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It's All About The Tasks! Automation, Firms, And Immigration

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It's All About The Tasks! Automation, Firms, And Immigration

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by

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It's All About The Tasks! Automation, Firms, And Immigration

Dedicated to my son, Jacob Emmanuel!

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ABSTRACT

It's All About The Tasks! Automation, Firms, And Immigration

By

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This dissertation was written as part of a broader interdisciplinary research agenda regarding the impact of the “fourth industrial revolution” on international affairs. In particular, I argue that we can look at the transformative effects of emerging technologies (e.g., automation and artificial intelligence (AI)) on labor, to account for important shifts in international norms and policies on questions that range from security to trade and immigration. Building on task-based literature from micro-economics and literature from international political economy that calls attention to the source of domestic political cleavages, in this dissertation I propose looking at the effects of emerging technologies, through their transformative effects on labor composition, on firm-immigration lobbying. To complete my research, I have constructed an original panel dataset consisting of a series of firm-level indicators. I rely on statistical analysis, including the use of an instrumental variable approach to run my regressions and address potential issues of reverse causality and omitted variable bias. By calling attention to how emerging technologies shape firms’ labor demand, we can understand their subsequent endorsement of international economic policies. My main claim is that automation, and other emerging technologies like AI have increased firms’ demand, reflected via lobbying, for non-routine immigrant workers.

Key words: Immigration, automation, lobbying, tasks, labor, firms

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CHAPTER 1. INTRODUCTION

Margaret Peters's (2017) book *Trading Barriers: Immigration and the Remaking of Globalization* sheds light on the often overlooked, endogenous relationship between immigration and trade. According to Peters, states can open their borders to the flow of labor (i.e., immigration) or the flow of either capital or goods, but not all three at the same time (Peters 2017, 4). While it may have been once more beneficial for industries to lobby for immigration to meet their production needs, they have increasingly reduced their immigration lobbying efforts in favor of open trade, firm mobility[1], and automation[2].

In this project I expand on Peters's analysis by looking at the effects of automation on immigration lobbying, as part of a broader research agenda aiming to provide greater theoretical and empirical analysis regarding how the "Fourth Industrial Revolution"[3] is transforming international political economy (IPE) and international relations (IR) more broadly. Economists like David Autor and Daron Acemoglu have presented ways of theorizing and measuring the effects of automation on labor by looking at the *tasks* performed by labor. This permits a distinction between *routine* tasks, which require the methodical repetition of unwavering procedure and *non-routine* tasks, those in which, "the rules [to perform a given task] are not sufficiently well understood to be specified by computer code and executed by machines" (Autor et al. 2003, 1283). We are more likely to

1 Understood as the ability of firms to produce outside their home country, otherwise known as foreign direct investment (FDI) (Peters 2017).
2 Automation entails reliance on machines, computers, robotics, artificial intelligence (AI), and other forms of mechanization or computerization to replicate human labor for the execution of tasks and industrial processes (Acemoglu and Restrepo 2018, 3).
3 The term "Fourth Industrial Revolution," is credited to the German engineer and economist Klaus Schwab, as way to characterize developments in new technologies like artificial intelligence (AI), robotics, autonomous vehicles, 3D printing and more executive, and the industrial, economic, social, and political consequences of these developments (Schwab 2015, 7).

see automation displacing labor from the performance of routine tasks, as machines can be programmed or engineered to be more efficient and effective in their replication to meet production needs than workers. By contrast, automation can have a *complementary* or *additive* effect (increasing demand for labor), in situations in which labor performs non-routine tasks. Thus, automation can both increase and decrease demand for labor, and thereby influence firms' demand for workers, including immigrant workers.

Among the most prominent actors lobbying for immigration are firms and trade associations that generally cite labor needs and concerns as motivations for their efforts to procure political outcomes that favor immigration. In this project I explore the link between the effects of new technologies like artificial intelligence (AI) and automation on firm's labor needs, and firm-immigration lobbying. I propose that utilizing a task-based approach permits us to better understand and identify why some firms are more likely to lobby for immigration than others.

1.1 Immigration through the Lens of IPE

In the context of IPE, particularly as articulated by the Open Economy Politics paradigm (OEP), many scholars have sought to identify which actors gain and lose from globalization policies like free trade. According to the first stage of OEP, we see actors mobilize resources in favor of, or in opposition to, international economic policies depending on whether a given policy stands to benefit, or undermine, the material interests of the actors in question (Lake 2009). While considerable attention has been given by IPE scholars to domestic-based cleavages on trade and finance, the question of immigration has been mostly overlooked by mainstream OEP and IPE scholars, or not given sufficient degree of scrutiny as finance and trade.

To some extent, particularly in the United States, the question of immigration tends to be analyzed through the lens of public opinion, ongoing political polarization, and congressional gridlock. Certainly, the question of what causes immigration policy is itself complex, which merits analysis of historical, institutional, and cultural trends. As with other nations in the Americas, along with countries like Australia and New Zealand, the United States started as a European Settler colony and upon achieving independence, featured varying episodes of mass immigration into the country.

Throughout its history, there have been varying levels of migration into the country, as well as changes regarding the dominant group migrating into the country. Thus, the United States went from being a hub for primarily Anglo-Saxon settlers, to a country that favored the entry of Protestants/Northern Europeans, to eventually opening up more to Europeans in general, and subsequently more open to people originating from non-European nations (Zolberg 2008). Throughout the country's history, there has also been variation in terms of the degree of openness/restrictiveness the country imposes to the entry of migrants (Zolberg 2008)and there have always been political, economic, and cultural debates regarding the merits and shortcomings of immigration. This dissertation does not question the validity of political culture and public opinion in the framing and implementation of past and present immigration policies.

At the same time, the current political environment in the United States is one in which political lobbying has become a political end in itself. (Drutman 2017). Although initially, lobbying was a way to achieve influence and access to lawmakers, in the last forty years, amid political decisions like *Citizens United v. FEC*, for example, political lobbying has become an institution in itself. Increasingly, many of the clients and their lobbyists have now become integral to the policy process itself (Drutman 2017). In a context in which lobbying matters, understanding how and why certain actors lobby the way they do, along with the issues they lobby for, may shed insights regarding these political issues. Even if there exists a political impasse on questions of immigration policy, exacerbated by the ongoing confluence of economic, cultural, and political factors, firms continue to be the dominant actors that lobby on immigration. In short, there are political economic outcomes that motivate certain firms to lobby on questions of immigration even in a climate in which there is a seeming paralysis when it comes to enacting significant policies on these issues. Thus, building on the logic of OEP, this dissertation looks at what it is that motivates these firms to continue lobbying on immigration even in the face of polarization and gridlock.

1.2 The Changing Face of Labor

Margaret Peters (2017) explains that firms' production needs have been pivotal in decisions regarding immigration to countries like the United States. In situations in which it was more advantageous for firms to rely on the mobility of labor into the United States (i.e., through immigration), firms were more likely to invest in political resources in favor of policies that enabled immigration. Since the 1980s however, amid the rise in globalization and the subsequent easing of cross-national flow of goods and financial capital, many firms have opted to pursue their labor needs via trade or by relocating production needs to nations where labor costs are lower. The more firms benefit from trade or relocating their production facilities overseas, the less likely they are to endorse immigration, and thus the easier it becomes for anti-immigration actors to impose restrictions on immigration (Peters 2017).

This does not suggest, however, that firms no longer support immigration. In situations in which firms' production cannot easily be met either by trade or by firm-relocation, it is more likely that firms will continue to support immigration to meet their production needs (Peters 2017). Part of Peters's analysis then considers on the types of situations in which firms may continue to benefit and thus openly endorse immigration politically. This dissertation complements Peters's work by reflecting on questions regarding the changing face of labor in countries like the United States. The central theme of this dissertation is to elaborate on the material factors that motivate some firms to continue endorsing immigration politically. In other words, if some firms continue to benefit from immigration to meet their production needs, what is it about the nature of these firms' production needs that propels them to continue to lobby for immigration.

As authors like Daron Acemoglu and David Autor's task-based models suggest, new technologies are increasingly altering the types of occupations that can employ workers in the United States. In situations in which machines and new technologies can replicate the tasks produced by labor, we are more likely to see machines replace workers. The introduction of machinery, though, can increase demand for other occupations or create entirely new occupations that employ workers. Understanding which types of occupations are likely to be displaced by technology, versus the types of occupations in which technology can increase demand for labor is significant for understanding the immigration lobbying patterns of firms. If firms can trade or relocate production, as Peters articulates, yet continue to lobby for immigration, is this because immigration continues to derive material benefit for these firms? If so, can we use the task-based model to explain the situations in which firms are more likely to lobby for immigration?

In this dissertation, I argue that task-based models can be used to explain immigration lobbying activity by firms, showing how immigration can be conceived of and analyzed through the lens of political economy. My main claim is that automation has increased firm demand, reflected via its lobbying, for non-routine immigrant workers.

1.3. Dissertation Overview

In the subsequent chapters, I develop the grounds that warrant this research project along with the analysis, findings, and interpretations of these findings. In chapter 2, I expand on the existing literature regarding OEP, and the place of immigration in the context of IPE and whether we can use IPE to analyze and explain immigration policy.

Chapters 3 and 4 serve as additional background chapters, where I further spell out the justification for this project. In chapter 3, I expand on the historical trajectory and developments in lobbying in the United States. Amid the ubiquity of political lobbying in the United States, understanding the source of variance in lobbying among large firms is significant for it gives us a sense as to what political outcomes firms are willing to accept, as opposed to those political outcomes over which firms are willing to incur large costs to overturn.

In chapter 4, I explain the main premises of the task-based models as used in economics. Essentially, in situations in which workers are engaged in routine activities or tasks, i.e., in situations where the nature of work can be codified and replicated mechanically or through an algorithm, we are more likely to see machines displace workers. By contrast, in situations in which workers are performing non-routine tasks, we are more likely to see complementary or even new demand for workers. While the use of technology varies significantly across economic industries and sectors, it is reasonable to assume that given the rapid advances in electronics, exemplified by Moore's Law, the diffusion of automation and new technologies occurs across all occupations. This assumption is significant because it means that we should be able to identify the displacement, complementary, and additive effects of technology on labor, irrespective of occupations, industries, or even skill level of workers.

In chapter 5, I formally present my main claims, namely that automation is likely to increase firm immigration lobbying for non-routine workers. In chapter 6, I elaborate on the main sources of data available for this project. While this project relies on observational data, I access different metrics from diverse sources like the Center for Responsive Politics, the Department of Labor, and U.S. Census Bureau. As this dissertation focuses on questions of technology, labor, and lobbying, I test my claims using longitudinal and panel data.

In chapter 7, I provide descriptive statistics showing correlations between non-routine foreign-born workers employed in certain firms, along with those firms' immigration lobbying track record. Then, in chapters 8 and 9, I lay out some inferential statistics along with some additional robustness checks showing a positive relationship between firms' capital investment, their reliance on non-routine immigrant workers, and their lobbying on matters of immigration.

Finally, chapter 10 concludes by summarizing the main lessons drawn in this project, a discussion on the limitations of this dissertation as well as the implications of this research for future studies regarding the effects of technology on international relations and international political economy. The conclusion also offers some thoughts about the importance of self-critique and reified theory.

CHAPTER 2. LITERATURE REVEW

This dissertation will build on the logic of the first stage of the open economy politics paradigm (OEP), aiming to evaluate the distributional consequences that automation has on domestic actors, and by extension, whether these distributional questions crystalize into domestic political cleavages regarding immigration policy. I build on the assumption that actors that materially benefit from policies, "are expected to expend resources in the political arena to obtain th[e] policy [in question] (as a shorthand, to lobby) up to the point where the marginal cost of that effort equals the marginal benefit (defined either as "more" of the policy or an increased probability of obtaining a fixed policy)" (Lake 2009, 226).[4] In essence, actors are rational and likely to lobby for policies that benefit their material interest, or lobby against policies that threaten those same interests.

In this section, I will review a number of the bodies of literature that have implications for my project. I will expand on two components in particular. First, can we understand domestic political cleavages regarding the question of immigration, expressed through political lobbying, as an extension of the material interests of domestic political actors? Second, can we factor in the effects of automation on labor, when assessing the discussions of political cleavages on immigration?

[4] OEP comprises three levels analysis, or stages. The first stage looks at how individuals or groups are affected by international economic policies, and thereafter, how domestic actors respond to those policies. The second stage of OEP, looks at how domestic institutions aggregate and mediate the preference of domestic actors. Finally, the third stage looks at how, once preferences aggregate at the national level, states then seek to negotiate and bargain internationally to obtain said preferences.

2.1 Material Based Sources of Domestic Political Cleavages

2.1.1 The Canonical Models

Neo-classical economic models like the Hecksher-Ohlin (HO) and Ricardo-Viner (RV) posit that nations will ultimately choose policies that maximize their economic interests and utility. Initially devised around the question of trade, the HO and RV models build on "neoutilitarian," rationalist, and materialist premises (Cohen 2019; Ruggie 1998). These models assert that nations will likely choose economic policies based on a logic of consequence, where it is assumed that actors (whether it is individuals, political institutions, or states) are rational and in pursuit of clearly defined material interests (Cohen 2019).

Because actors are rational, the choice of international policies, like trade for example, will rest on whether those policies maximize their utility. However, both models posit that irrespective of the rationality of actors, invariably policies will produce outcomes that materially benefit some actors, at the expense of others. In short, although actors are rational in the pursuit of their interest, international economic policies ultimately end up creating winners and losers at a domestic level (Grossman and Helpman 1994).

Where these models differ is in terms of explaining out who is more likely to "win" from the implementation of a given economic policy as opposed to who is more likely to "lose" from the same policy. In the case of the Hecksher-Ohlin model, and its corollary the Stolper Samuelson theorem (HO-SS), it is assumed that nations will ultimately choose to develop and specialize in the production of goods and services, in which they can more effectively utilize their factors of production (land, capital, or labor). Usually, this means that nations will produce goods and services that exploit their relatively more abundant factor of production. For example, a capital-abundant nation may use its resources more efficiently if it builds and eventually exports capital-intensive goods (e.g., ambulances), while it then opts to import bananas (whose production is more labor-intensive). The reverse would be the case in nations where labor is the relatively abundant factor.

The SS theorem adds to the logic of HO, by spelling out the distributional consequences where the scarce factor sees a reduction in income, while the abundant factor sees an increase. The HO-SS model assumes that factors of production can freely move across industries, meaning that workers could one day work in one industry and later in another, and also that factor returns like wages and the rental rate of capital are identical across industries in equilibrium (Kim and Osgood 2019).

Based on the logic of HO-SS, coalitions pushing for, or opposing, international economic policies may mirror class-based cleavages where factor-owning classes—i.e., land, labor, and capital—may find themselves at odds with one another (Rogowski 2020). If economic policies are taken to exploit a nation's factor endowment, we are more likely to see class-based cleavages where the more abundant factor of production will likely benefit and support trade liberalization while the scarce will likely lose out and thus oppose it (Milner and Kubota 2005).

In assessing the question of immigration, some scholars have used the logic of HO-SS to assess the distributional consequences of immigration on domestic actors (Scheve and Slaughter 2001). In more advanced economies like the United States, where the relatively abundant factor tends to be capital, it is proposed that support for and opposition to immigration will reflect class-based cleavages (Mayda 2006; Midford 1993; Scheve and Slaughter 2001). Capital-owners may stand to gain from immigration, irrespective of the latter's skill-level, as immigrants may both further the interests of capital owners and provide an economical alternative to reliance on native-born workers (Mayda 2006; Midford 1993; Scheve and Slaughter 2001). By contrast, workers, especially low-skilled workers within these capital-intensive nations, should be more likely to oppose immigration policy for fear of competition over employment as well as fear that immigrants may also contribute to the depreciation of wages (Scheve and Slaughter 2001).

In contrast to the HO-SS, the Ricardo-Viner (RV) model assumes that at least some factors of production are immobile across industries, i.e., that they are specific to a particular industry (Kim and Osgood 2019). Hence, RV suggests that domestic cleavages on questions like trade and immigration are more likely to be based along entire sectors, comprised of both owners of capital and labor. Therefore, rather than class-based cleavages, we are expected to see sectoral-based cleavages in matters of international economic policy, including immigration (Alt et al. 1999).

For example, individuals who form part of a growing economic sector are more likely to support immigration, since the influx of migrants may benefit both owners of capital and native-born workers; especially in situations where the presence of immigrants permits native-born workers the opportunity to aspire for higher paying jobs (Bilal, Grether, and de Melo 2003). By contrast, individuals working in shrinking sectors may oppose immigration, due to fear of competition over limited employment or depreciating wages (Dancygier and Donnelly 2013).

The question of whether HO-SS or RV better explains policy-based distributional outcomes and, thus, domestic political cleavages, may ultimately depend on whether domestic factor mobility is possible or not (Alt et al. 1996; Hiscox 2002; Imai and Tingley 2012). Class-based cleavages may be more pronounced in situations in which levels of factor mobility within an economy are relatively high, while sectoral or industry-based conflicts appear when levels of mobility are low (Hiscox 2001). In this sense, low-skilled immigrants may compete for certain jobs with native-born workers, particularly those without a college degree. However, any negative effect derived from low-skilled immigrants may be mitigated depending on the extent to which there is mobility across sectors for native-born workers (Card 2001).

2.1.2 Firm Heterogeneity

The degree to which the canonical models accurately capture the source of material-based domestic political cleavages has been challenged and questioned by several empirical accounts (Madeira 2016). Starting with the question of trade, firms[5] rather than factors or sectors tend to be the dominant actors who benefit or lose from trade liberalization. And, usually it is larger more powerful firms that benefit from the liberalization of trade rather than smaller firms (Kim and Osgood 2019; Madeira 2016). To some degree intra-industry-based cleavages are in part furthered by changes in consumer preferences, which may value variety over specialization of consumer goods (Krugman 1980). For example, the United States and Australia import wine from one another despite the fact that both nations produce their own wine. Accordingly, the impetus to import wine in these cases is not due to factor scarcity nor sectorial efficiency. Instead, the exchange of wine occurs, because firms in each country increase their revenue by selling their products in both markets (Kim and Osgood 2019, 3). Therefore, empirically we are more likely to witness intra-industry-based cleavages pitting firm against firm rather than class-based or sector-based cleavages in matters of economic policies like trade (Madeira 2016).

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[5] We can think of *firms* primarily as business that produce goods and services (Peters 2017, 3).

Immigrants can and often do play a role in furthering changes in cross-national demand for certain consumer goods. On the one hand, immigrants often seek ways to access consumer products from their home country, in their host country (Blanes 2005; Faustino and Proença 2015). On the other hand, immigrants can also help to popularize consumer goods from their host nation in their country of origin (Blanes 2005; Faustino and Proença 2015). Thus, larger firms may be more capable and better suited—in part due to patent-ownership or rights of distribution—to meet these shifts in the cross-national demand for certain consumer goods than smaller firms, with the latter often finding themselves competing against the influx of consumer products.

In addition, very large and powerful firms have increasingly benefitted from exploiting international supply chains that maximize returns to scale. Essentially, large companies may profit from offshoring portions of the production of goods, to other nations, thereby creating production-sharing networks and integrated supply lines (or intra-firm trade), which reduce production costs and maximize returns to scale (Chase 2005; Melitz 2003; Feenstra and Hanson 2003).

The relationship between immigration and international supply chains is complex, since reliance on these supply-chains can reduce the demand for labor, especially low-skilled labor, in advanced economies like the US, as it is often low-skilled labor-intensive activities that are out-sourced (Peters 2017). However, there is evidence that immigrants can provide *ex-ante* benefits to some of these larger firms. Immigrants can generate useful and necessary information to large firms about what countries may be more suitable to consider as part of their cross-national supply chains (Egger, Erhardt, and Lassmann 2019).

In short, larger firms may stand to gain materially from immigration in ways that smaller firms do not. What is less clear, is whether any of the material benefits derived by firms from immigration translate into active support and lobbying for immigration by these same firms. In essence, even if immigration benefits the material interests of larger firms, do we then see firm-based cleavages on immigration, with larger firms lobbying for immigration, with smaller ones lobbying against, based on the information and distributional networks immigrants generate for the larger firms?

2.1.3 Other Material Explanations: Fiscal Burden

Opposition to immigration may be an outcome of the fiscal effect that immigration poses for both high and low-income earners. The rationale here is that immigration, especially low-skilled and low-income immigration, may translate into further demand for social services and programs (Hanson, Scheve, and Slaughter 2007). As demand for social services increases, due to immigration, so too would the tax-burden placed on high-income earners, who would then see immigration as a liability (Hanson, Scheve, and Slaughter 2007). By contrast, if immigrants demand more social services, the logic goes, this may generate competition between low-income native-born workers and poorer immigrants for access to those services (Hanson, Scheve, and Slaughter 2007).

2.2 Non-materialist Explanations

Some scholars question the extent to which domestic political cleavages on economic policies, from trade to immigration, are due to the distributional effects that those policies have on the material interests of domestic actors. Survey research has suggested that usually there are more normative, ideational, or ideological elements that influence opinions on questions like trade or immigration (Borjas et al. 1997; Harell et al. 2012; Hainmueller and

Hiscox 2010; Hainmueller, Hiscox, and Margalit 2015; Inglehart and Norris 2017; Mansfield and Mutz 2009). These non-material explanations sometimes feature a logic of appropriateness, one in which an actor's socialization or cognitive biases more accurately reflect the rationale behind differences in opinions on economic policies in general. Rather than assuming that individuals embody the utility-maximization of the *homo economicus,* we can think instead of individual behavior being socially derived, often acting within the limits of bounded rationality or locked into particular patterns due to socialization (Chwieroth and Sinclair 2013; Cohen 2019).

According to these non-materialist explanations, the extent to which the public is fully cognizant or aware of the effect that a given policy may have on their overall material wellbeing, seems to be based more on generalized beliefs and fears about the status of the national economy—i.e., socio-tropic concerns—like rising taxes, job competition, and general prejudice against immigrants (Citrin et al. 1997; Mansfield and Mutz 2009). In essence, general opposition to immigration policy is based more on the prejudice or belief about the effect that immigrants *could* have on the national economy, rather than the actual measurable effects that immigrants *do* have on the livelihood of native-born workers.

For example, in countries like Canada and the United States, public opinion surveys often rank greater support for high-skilled immigration over low-skilled immigration (Ctirin et al. 1997; Harell et al 2012; Hainmueller and Hiscox 2010; Hainmueller, Hiscox, and Margalit 2015). However, it seems that this bias in favor of high-skilled immigration stems more from a perception or prejudice that regards high-skilled immigrants as assets, while low-skilled immigrants as liabilities. While most evidence suggests that low-skilled immigration pose little to no discernable adverse effect on the wages, taxes, or employment opportunities of native-born workers, the skill-bias persists (Borjas et al. 1997; Rodrik 2018).

Increasingly, appeals to, “fairness” combined with growing resentment against foreigners have exacerbated xenophobic attitudes across nations (Borjas et al. 1997; Rodrik 2018). Support for nationalist right-wing populist, and anti-immigrant candidates, like Donald Trump in the US and Jair Bolsonaro in Brazil, has increasingly featured cleavages that could be characterized more as generational and normative than materially based (Inglehart and Norris 2017; Rodrik 2018). On average, older voters have exhibited greater concern and preoccupation with questions of economic scarcity as well as would-be threats to their economic livelihood. By contrast, younger voters have exhibited greater concern with *post-material* issues like tolerance, equality, and care. In this context, it is worth noting that figures like Trump have resonated more among older than younger voters (Inglehart and Norris 2017).

2.3 Trading Barriers

Margaret Peters (2016; 2017) provides significant insights regarding the endogenous yet overlooked relationship between immigration and trade. Peters first asks us to consider two empirical puzzles. First, there is a noticeable inverse relationship between trade and immigration policies. Nations have at times relatively open borders to the entry of people, i.e., to migrants, but relatively closed borders to the flow of goods and financial capital. At other times, nations have opened up their borders to trade and financial capital mobility but closed their doors to immigration. What states have not done is open their borders simultaneously to trade, financial capital mobility, and immigration (Peters 2017). Second, why is opposition to immigration usually more pronounced among domestic actors than opposition to trade?

Materialist models fail to address these puzzles. Any potential liability that immigrants could pose to domestic actors (e.g., competition over jobs, depreciation of wages, or increased demand for welfare services) can also be threatened by trade. Theoretically, both trade and immigration may have similar distributional consequences among domestic actors, yet opposition to immigration is more pronounced than opposition to trade across domestic actors (Goldstein and Peters 2014; Peters 2017).

If we look at non-materialist models, we should also expect to see that appeals against "unfairness" or "undue" competition for native-workers to be equally voiced against trade as against immigrants (Goldstein and Peters 2014; Peters 2017). While figures like Donald Trump have been vociferous in their condemnation of trade and immigration, it stands that more often than not, opposition to immigration is more pronounced than opposition to trade liberalization (Peters 2017). Even if xenophobia and bigotry can partially explain why there is greater repudiation of immigration than trade, generalized prejudice against foreigners does not explain the inverse relationship between trade and immigration policies (Peters 2017). Despite the ever presence of nativism and anti-immigrant rhetoric within the United States, the fact remains that American history has featured episodes with more liberal immigration policies, on the one hand, along with more restrictive policies when it comes to trade or international financial capital mobility, on the other hand (Peters 2017). In short, public opinion is at the very least split on questions of migration and cannot account for the historic endogenous relationship between trade and immigration.

2.3.1 Firms Matter

To better understand the relationship between immigration and trade (along with firm mobility)[6] policy, we need to focus on firms and their policy preferences. The question of trade and immigration is not merely incidental but one that is in part related to the net benefits derived from certain production strategies. It used to be the case that the movement of physical capital (e.g., machinery) was both difficult and expensive. The productive interests of firms were better met at this time by increased reliance on labor rather than moving physical capital (Peters 2017). According to Peters, when the material interests of firms were more adequately met by the import of labor (i.e., immigration) firms were often at the forefront in terms of domestic support for immigration (Peters 2017).

However, developments exogenous to firms ultimately shifted firms' production strategies, thereby also shifting firms' policy preferences (Peters 2017, 4). Changes in policies that reduced and sometimes removed restrictions on the cross-national flow of goods, along with advances in communication and transportation technology, created new production opportunities for firms along with greater returns to scale. As borders began to open to the flow of goods and financial capital, firms began shifting production preferences in favor of trade and financial capital mobility. The more firms became reliant on trade or firm mobility to meet their production needs, the less reason they had to push for policies facilitating the procurement of labor, including immigration (Peters 2017, 19).

Therein lies the inverse relationship between trade and immigration. When the net-benefits derived from immigration outweighed those of trade, firms pushed for border openness to migrants. But once the net-benefits derived from trade and capital liberalization

[6] Peters defines firm mobility as the decision and practice employed by firms to move production from industrialized countries to nations where the costs of labor are cheaper (Peters 2017, 3).

began outweighing those of immigration, firms began pushing more for policies facilitating trade and firm mobility, reducing their support for immigration, in particular of low-skilled immigration.

Moreover, technology has permitted firms also to produce more, albeit with less labor, which further diminished firms' demand for labor in advanced economies, native-born or immigrant. While not all firms necessarily shifted their production strategies, a significant number of firms opted to meet their production needs either through trade, firm mobility, or labor-replacing technology, which significantly reduced these firms' policy support for immigration (Peters 2017, 16-17).

In essence, firm lobbying for immigration has since the late 1970s contracted, in particular for low-skilled immigration. The declining support for immigration has had two effects. First, it has made immigration move from an economic issue to a social one (Peters 2017). While some firms continue to lobby for immigration, cleavages have increasingly mirrored social or cultural groups that appeal more to certain national aspirations than economic ones (Peters 2017). Second, declining firm support for immigration has pressured politicians and policymakers to both ensure the interests of firms are met (in the form of trade and firm mobility), on the one hand, while attempting to assuage their constituents that their jobs are "safe from competition," on the other hand. In short, politicians may be willing to open borders to low-skilled labor and immigration at the expense of trade or firm mobility, or the reverse, but rarely all three at the same time.

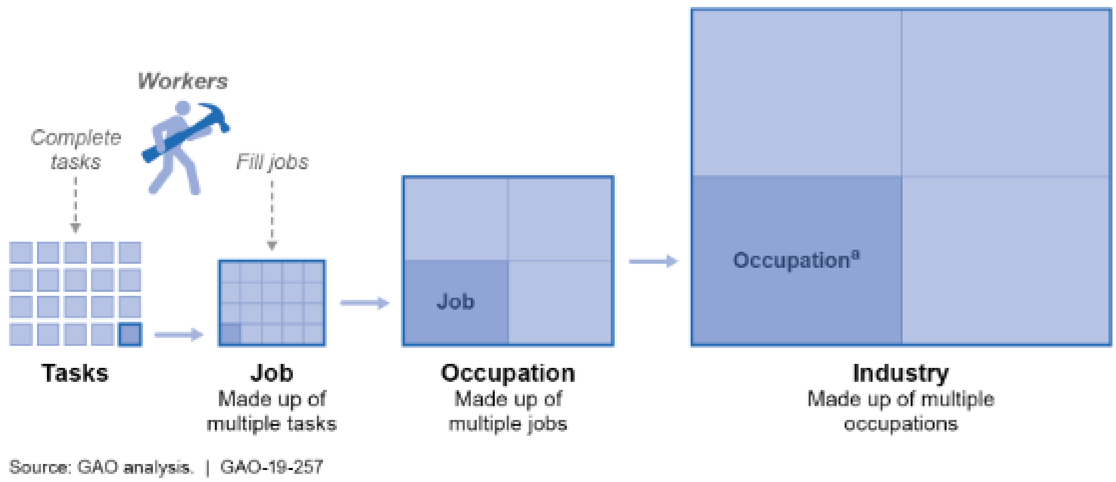
2.4 Reflecting on Automation

Peters suggests that in advanced economies like the United States, automation, trade, and firm mobility are essentially substitutes for labor, especially low-skilled labor. The more firms automate, trade, or outsource production, the less likely it is that they will lobby for immigration. Accordingly, new technology, "allows firms to do more with less labor, reducing their incentive to lobby for immigration" (Peters 2017, 4). By contrast further reliance on labor-saving technology may increase demand for high-skilled workers, and by extension firm demand for high-skilled immigration (Peters 2017, 24-25). However, the effects of automation on labor are more nuanced than those assumed by Peters, mainly because the effect that technology has on demand for labor is one that is contingent on the *task* being performed by labor, rather than the *skill possessed* by labor.

We can think of a *task* as a type of activity that constitutes a logical and necessary step in the performance of work by a worker (Office and Administration 1991). A *task* entails the exertion of human effort (physical or mental) to accomplish a specific purpose (Office and Administration 1991). As Figure 2-1 shows, we can think of any type of work activity as fundamentally completing a series of tasks, whether it is writing reports, picking berries, or prescribing medicine, these are all examples of tasks inherent to lines of work. By extension, we can think of an occupation as the common set of tasks that are performed by labor that share similar objectives, methodologies, materials, products, worker actions, or worker characteristics (Office and Administration 1991). Thus, in any given occupation, labor performs a series of interrelated tasks[7] (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor and Dorn 2013; Dao, Das, and Koczan 2019; Frey and Osborne 2017).

[7] For example, in the *Wealth of Nations*, Adam Smith shows how the process of manufacturing pins is reduced and atomized into a series of tasks that include drawing wire, straightening it, cutting it, sharpening its point, and grinding the head, just to name a few (Smith, 1979, 14-15). These tasks can be accomplished by a combination of human labor and machines. In some cases, machines may be more efficient, effective, and economical in the reproduction of a given task. However, in other cases, labor may actually be more advantageous than machinery for the production and completion of other tasks.

Figure 2-1: The Structure of Employment, from Work Task to Industry.



Conceptualizing the relationship between automation and labor in terms of *tasks,* reveals that automation is more likely to replace, or substitute, human labor in situations where workers perform a task that can be specified, coded, programmed, or mechanized, to the point that a machine can then fully reproduce the task in question. That is, machines are more likely to replace labor in the reproduction of *routine tasks* (Acemoglu and Autor 2011). As machines become more effective, efficient, and economical in the reproduction of these *routine tasks*, the more they stand to displace (or replace) human labor from the reproduction of these tasks (Autor, Levy, and Murnane 2003; Autor, Dorn, and Hanson 2015; Frey and Osborne 2017).

However, in other instances, the introduction of technology that automates the production of certain tasks can complement or even create entirely new tasks for labor. The extent to which automation has a positive impact on demand for labor usually rests on labor components such as situational adaptability, visual and language recognition, and in-person interactions. That is, automation complements labor in the performance of *non-routine* tasks (Acemoglu and Autor 2011). From both a technical and economic point of view, it becomes harder for machines to replicate or mechanize these *non-routine* tasks. Nevertheless, there is a seeming equilibrium regarding technology and firm demand for labor. While technology can replace labor in the reproduction of certain *routine* tasks, this may also be accompanied by deepening demand for *non-routine* tasks.

Second, differentiating between *routine* and *non-routine* tasks reveals that many of the occupations constituted by *non-routine* tasks are often found at the "poles" of the income/skills distribution. That is, low-skilled labor and high-skilled labor are both more likely to be working in occupations characterized as being *non-routine*. Moreover, since the 1980s, immigration to the United States has been characterized for being comprised of mostly non-routine workers mirroring the demand for non-routine occupations that seeks both high and low-skilled workers (Basso, Peri, and Rahman 2020).

2.5 Does Demand for Low-Skilled Labor Translate into Demand for Low-Skilled Immigration?

Peters acknowledges that in some economic sectors in the United States demand for low-skilled labor may remain high. However, even if demand for low-skilled labor remains stable, or even increases for some firms, this does not necessarily translate into support from those firms for immigration. Increasingly, firms can rely more on alternatives to low-skilled immigration, for example, by employing native-born who may have lost their job due to overseas firm-relocation, trade, or automation (Peters 2017, 78).

However, it should be noted that automation is not always the cause for contractions in immigration labor as it has been at times its consequence. For example, in 1964 the United States ended the Bracero Program[8], thereby reducing the supply of seasonal (low skill)

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[8] The Bracero Program entailed a series of laws and bilateral agreements between Mexico and the United States that spanned between 1942 and 1964. The primary goal of the Bracero Program was to regulate

agricultural Mexican workers into the US. Although many firms benefitted materially from the Bracero Program, once the program was terminated, rather than increase their reliance on native-born workers, these firms opted to adopt machinery to meet their production needs (Clemens, Lewis, and Postel 2018). Thus, even if policies contravene firm demand for low-skilled immigration, the fact that they can find substitutes to immigration means that they will be less likely to mobilize and lobby for low-skilled immigration (Peters 2017).

However, since the 1980s immigrants have supplied labor in mostly different occupations than native-born workers (Peri and Sparber 2009). Additionally, on average, low-skilled immigrants have exhibited greater willingness to relocate geographically within the United States, amid changes in labor demand, than native-born workers (Cadena and Kovak 2016). There is even evidence that the influx of both high and low-skilled immigration may have helped generate greater demand for ancillary goods and services employing middle-skilled (often native-born) labor (Basso, Peri, and Rahman 2020). Overall, by complementing demand for non-routine work, both low and high-skilled immigrants have also helped increase demand in consumption of goods and services, which down the line, help increase employment opportunities for native workers (Basso, Peri, and Rahman 2020).

Because immigrant labor often congregates in certain occupations that are in general non-routine, I propose that automation can have a positive effect on the demand for labor, which in certain cases also translates into demand for *immigrant* labor. In the next two chapters, I will provide additional justification for my project. First, I will expand on the significance and ubiquity of lobbying, and then elaborating on the theoretical model I will

bilateral flows of temporary low-skill labor. During its existence, the Bracero Program mostly featured Mexican workers working in the agriculture sector (Clemens, Lewis, and Postel 2018, 1469).

use to account for how automation can increase demand for labor and in so doing why it can also increase demand and firm lobbying for immigration, both low- and high-skilled.

CHAPTER 3. LOBBYING

In this chapter, I will provide important context and background elements on lobbying. In particular, I will expand on the significance that firm lobbying has in contemporary US politics. Lobbying has become more than a mere activity through which economic and social actors voice or promote policies friendly to their interests. Increasingly, lobbying has become an activity deeply tied to the policy process in the United States as policy and decision makers have become dependent on firms and other powerful lobbying actors in the formulation and implementation of policy. To look at lobbying reveals, in some respect, the causes for why certain political outcomes materialize but not others.

3.1 Lobbying

In a very general sense, *lobbying* refers to any activity which tries to persuade someone in authority, for example an elected or appointed member of government, to support laws or rules that give the person, group, organization, or industry a political advantage, or oppose what may be disadvantageous (Drutman 2017). Lobbying can be regarded as spending political capital, through which actors like firms express their likelihood or willingness to support, endorse, or oppose a given policy maker, to ensure that the latter produces favorable political decisions for the former (Peters 2017).[9]

In the United States lobbying entails more than donating money to political campaigns (i.e., campaign contributions) (Drutman 2017, 16). In addition to campaign contributions, firms can also signal their policy preferences to policymakers through votes

[9] It is worth noting that the legal definition of what activities constitute as lobbying varies from nation to nation (Baumgartner and Leech 1996). The implication of this is that some types of political activities may be categorized as lobbying and therefore permissible in some jurisdictions, while impermissible in others. Thus, any cross-national account of lobbying would have to factor these differences when it comes time to comparing the ways through which firms assert their preferences cross-nationally.

from their employees, congressional testimonies, publicity and public relations campaigns, and even potentially through bribes (Peters 2017, 20-21). The closer policy makers endeavor to fulfill the firm's policy preference, the more material support the firm will provide for said policymaker (Peters 2017). Lobbying, thus, reveals the extent to which firms are willing to incur costs and invest resources in the political arena under the hope that they will shape policies to be favorable to their interests (Lake 2009; Grossman and Helpman 1994, 2002).

Whether it is possible to determine all existing channels through which, firms influence policy makers may not be entirely clear. For example, while activities like *quid-pro quo* or blackmail are illegal, whether domestic actors recur to these in their pursuit of influencing policy makers is another story. For the purpose of this dissertation though, I will neither deny nor speculate on the extent to which these illicit activities operate within the policy process, given the difficulty in obtaining and verifying reliable data.

3.2 The Growth and Ubiquity of Lobbying

In the United States, lobbying has become a multibillion-dollar industry, which in the last thirty years has developed unprecedented levels of reach and influence (Drutman 2017). Especially since the 1990s, firms in particular have gone from being largely peripheral political actors (that would lobby sporadically and usually as part of trade associations), to becoming ever-present actors incurring lobbying expenses worth millions of dollars annually (Drutman 2017). Consequently, through their lobbying efforts firms have invested and involved themselves not only financially, but also intellectually in the policy process.

Through their lobbying efforts, firms have been able to clinch direct access and influence on policy circles in Washington D.C. enabling a proactive collaboration with policy makers in the elaboration and enactment of new policies, or the amendment or repeal of old policies. In short, the growth of firm lobbying over the last thirty years has made firms indispensable political actors who are often considered and consulted when political decisions are made on a wide range of issues, including immigration (Drutman 2017).

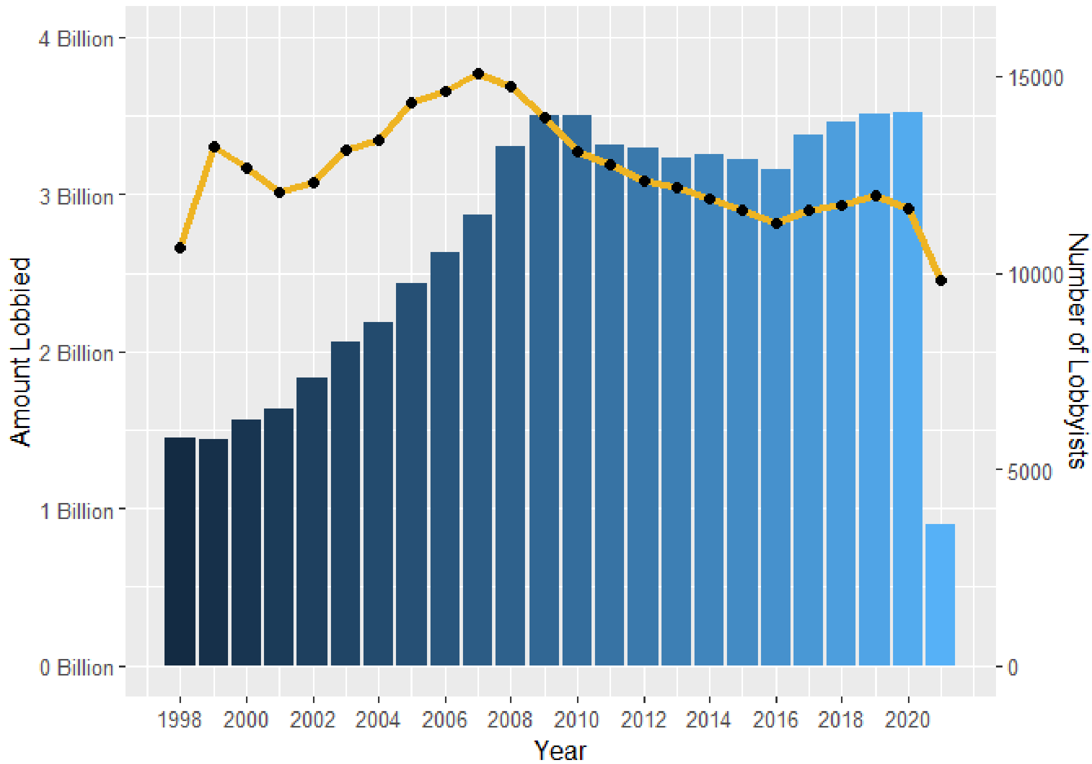
Firms tend to lobby through professional lobbyists who represent their priorities and interests politically. Lobbyists fulfill several functions, they can serve as de facto adjunct staff for congressional offices, draft bills, provide testimony, and help push for legislation (Drutman 2017, 1). In short, through lobbyists, firms can provide policy expertise and intellectual support (in the form of think tanks) to policy makers. Lobbyists can also help spread a particular message through targeting advertisement and op-eds, build political coalitions, help mobilize grassroots organizations, and discredit firms' opponents (Nownes 2006).

Presently, firms can hire lobbyists through one of two ways (sometimes both): in-house lobbying or contract lobbying (Nownes 2006). When firms rely on in-house lobbying, they hire lobbyists to work as fulltime employees of the company, working under a wing or branch of the company, to represent their political interests, and often represent their employer exclusively (Nownes 2006). By contrast, contract lobbying involves the hiring of lobbyists who work for a separate lobbying-firm that offers their lobbying expertise and services to clients and thereby lobby on behalf of the latter (Nownes 2006).

Generally, it is more likely for in-house lobbyists to be employed by larger and more economically solvent firms (especially those capable and willing to spend over 1 million US dollars annually in lobbying) (Drutman 2017). The majority of firms, though, tend to rely solely on contract lobbying since a) their political objectives are limited, or b) because contract lobbying can be a more economical alternative for a firm to lobby (Drutman 2017).

As a result, most lobbying is carried out by contract-lobbying to the point that even larger firms tend to combine in-house lobbying as well as hiring contract lobbyists (Drutman 2017).

Figure 3-1: Total Annual Lobbying Spending (Not Adjusted for Inflation) & Registered Lobbyists[10]



Source: https://www.opensecrets.org/federal-lobbying

As Figure 3-1 shows, there has been a pronounced increase in the amount of money spent on lobbying in general, as well as in the overall number of lobbyists, especially when we compare political lobbying in 1998 and 1999 with years like 2010 and 2018.[11] The blue bars in Figure 3-1, represent the total lobbying spending by year (in billions USD not adjusted for inflation), and the golden line represents changes in the number of lobbyists. While there has been variation in terms of the lobbying expenditures and the number of

[10] Data from the Center for Responsive Politics (CRP) used to make this figure is based on data from the Senate Office of Public Records.

[11] Figure 3-1 shows the annual amount spent on lobbying between 1998 and 2018.

lobbyists employed, Figure 3-1 shows that lobbying has become a multi-billion-dollar industry, with the number of lobbyists hired somewhat mirroring lobbying amounts trends.

In many ways, the rise in lobbying as a political activity has become an end in itself. The profitability and prominence of political lobbying has invariably altered the policy environment. Not only has the number of lobbyists and the number of political issues lobbied on increased, but lobbyists have also become part of the policy formulation landscape (Hall and Deardorff 2006). The more money is spent on lobbying the more lucrative lobbying becomes as a work option for political insiders ranging from former congressional staffers, former members of Congress, former bureaucrats and civil-servants, and other types of political insiders finding employment as lobbyists (McCrain 2018).

The more lucrative lobbying becomes as a business, the more policymakers depend on the expertise of lobbyists in the crafting, passing, and implementation of policy (Drutman 2017, 18). In fact, political lobbying has become so ubiquitous that policymakers are not only more sensitive to lobbying but increasingly dependent materially -- and, more importantly intellectually -- to the input of lobbyists for the development, passing, and implementation of policies (Drutman 2017, 18).

The pervasiveness and ubiquity of lobbying has also complicated what is necessary for firms to have access and influence over policy makers (Kerr, Lincoln, and Mishra 2014). For lobbying to be a fruitful investment, firms must properly identify and hire the right lobbyists for their specific political objectives, elucidate and coach said lobbyists about the firm's political interest, develop a lobbying agenda, identify potential allies and opponents and understand what they are lobbying for, and single out policymaker(s) that are more likely to favor or be sympathetic in advancing the firm's policy objectives (Kerr, Lincoln, and

Mishra 2014, 344-345). In short, the returns on investment of political lobbying may neither be automatic nor immediate. Thus, the "costs" that firms must incur in order to ensure favorable political outcomes can act as a barrier to smaller and even mid-size firms. The more firms spend on lobbying, the more lobbying benefits those actors who are *already* heavily invested in political lobbying (Bombardini 2008; Kerr, Lincoln, and Mishra 2014). In short, the ubiquity of political lobbying has also made influencing political change harder and costlier, especially for firms that do not have a history of lobbying, given that change would entail diverting more resources (material and intellectual) to ensure proper expertise as well as access to policymakers (Baumgartner et al. 2009).

Lobbying incumbency, therefore, is a good indicator of how influential an actor is politically in the first place, as well as a predictor of whether this actor will lobby in the future (Drutman 2017; Kerr, Lincoln, and Mishra 2014). Hence, we are more likely to observe the lobbying behavior of larger and more solvent firms. Nevertheless, even amid the costliness inherent to lobbying, often smaller and even mid-size firms may join larger trade associations (organizations that represent business within a given industry) as a means of overcoming collective action obstacles to their individual lobbying, and thereby aggregate their common interests via reducing lobbying costs (Baumgartner et al. 2009; Kerr, Lincoln, and Mishra 2014; Peters 2017).

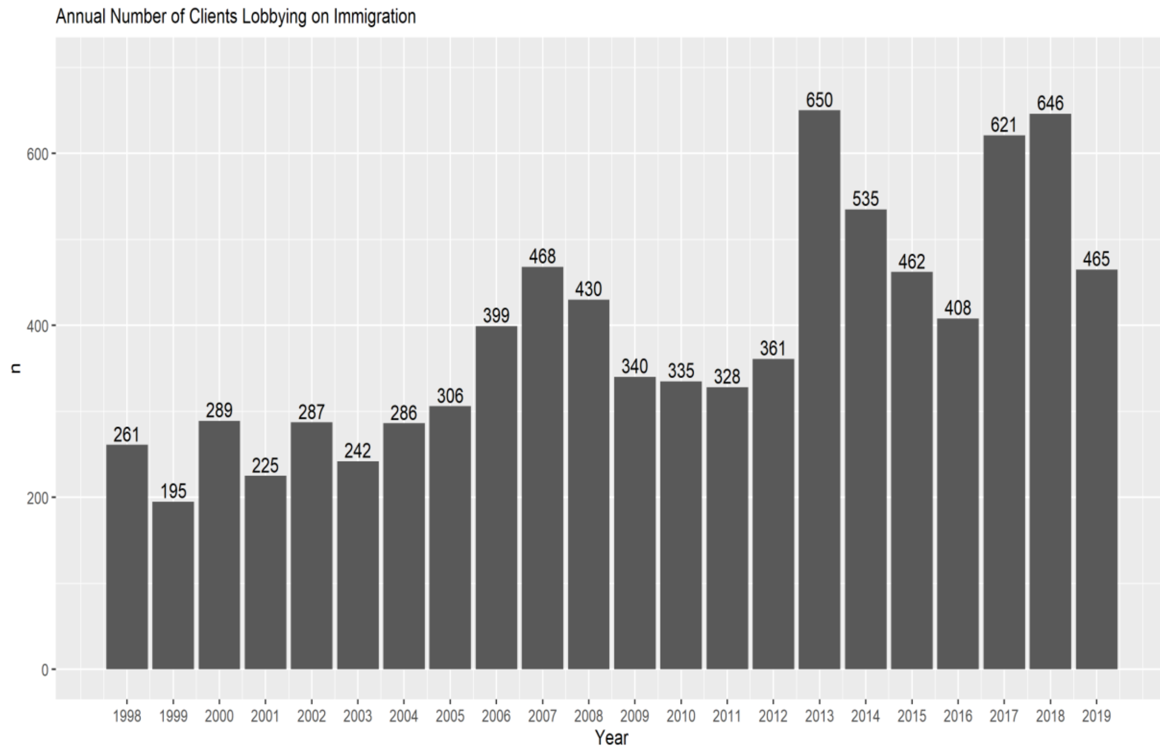
3.3 First Stage of OEP and Lobbying

Within the literature in international political economy, particularly within the context of the open economy politics paradigm (OEP), lobbying is an activity through which domestic actors voice their preferences with respect to international economic policies (Grossman and Helpman 1994; Lake 2009). As discussed in Chapter 2, the logic of OEP posits that actors who gain materially from policies that open up borders (whether it is to the flow of goods, financial capital, or migrants) are more likely to invest political capital, and therefore, lobby in favor of these policies (Grossman and Helpman 1994, Lake 2009). By contrast, those actors who stand to lose materially from the same policy are more likely to lobby against said policy.

According to the logic of the "New" New Trade Theory (NNTT); international policies are more likely to produce cleavages (i.e., division in terms of support for/opposition to a given policy between domestic actors) due to existing asymmetries between firms in terms of their size and economic clout. In short, NNTT asserts that domestic cleavages on globalization policies are inter-firm based, with sometimes firms from the same economic industry disagreeing and competing, via lobbying, with regards to a specific policy (Madeira 2016).

For example, larger more solvent firms are more likely to favor free trade (as this would allow them to export more to other markets), while smaller firms would be less likely to benefit from free trade (given that more firms (domestic and international) would now be able to compete in the same market) and thus lobby against free trade. Given the pervasiveness and ubiquity of lobbying we can ask ourselves about the nature of firm-based cleavages when it comes to policies regarding immigration. According to Peters, these cleavages are likely to derive between firms that can trade/relocate their production overseas, and those who are less likely to do so (Peters 2017). However, many firms that relocate their production can at times also be active promoters of immigration, as evidenced by Table A-1 in the Appendix, where we see large companies like Microsoft, that often have subsidiaries and suppliers around the world, being among the top promoters of immigration also.

Figure 3-2: Annual Number of Immigration Lobbying Clients



Source: https://www.opensecrets.org/bulk-data

3.4 Immigration Lobbying

Indeed, in the case of Microsoft, it may be that production requiring more high-skilled labor is based in the United States, given greater reliance on capital to meet production requirements, thereby prompting these firms to rely on higher-skilled workers coming to the United States (e.g., temporary workers who are granted an H-1B visa). Conversely, the production of lower-skilled services may be outsourced overseas to countries with lower labor costs. Nevertheless, even if Microsoft relies more on hiring high-skilled immigrant workers, we also know that low-skilled sectors like agriculture are more likely to lobby favorably for immigration. Thus, if we are to understand the root of firm-based political cleavages regarding immigration, we should be able to find the common link or theme that would unite more high-skilled employers like Microsoft with low-skilled employers in agriculture, regarding their preference for immigrant workers.

Figure 3-2 summarizes the total number of clients (e.g., Microsoft) that listed immigration as a lobbying issue. Figure 3-2 counts only final report[12] submissions between 1998 and December 31, 2018, utilizing data from the Center for Responsive Politics (CRP). As can be seen, there is variation in terms of the number of clients that lobby from year to year, along with what appears to be an upward trend in immigration lobbying.

In Figure 3-3 we can see the top ten economic sectors that lobbied most immigration reports between 1999 and 2017. Figure 3-3 represents the aggregation of all lobbying activity between 1999 and 2017 conducted by firms and/or trade associations within the same NAICS economic sector.[13]

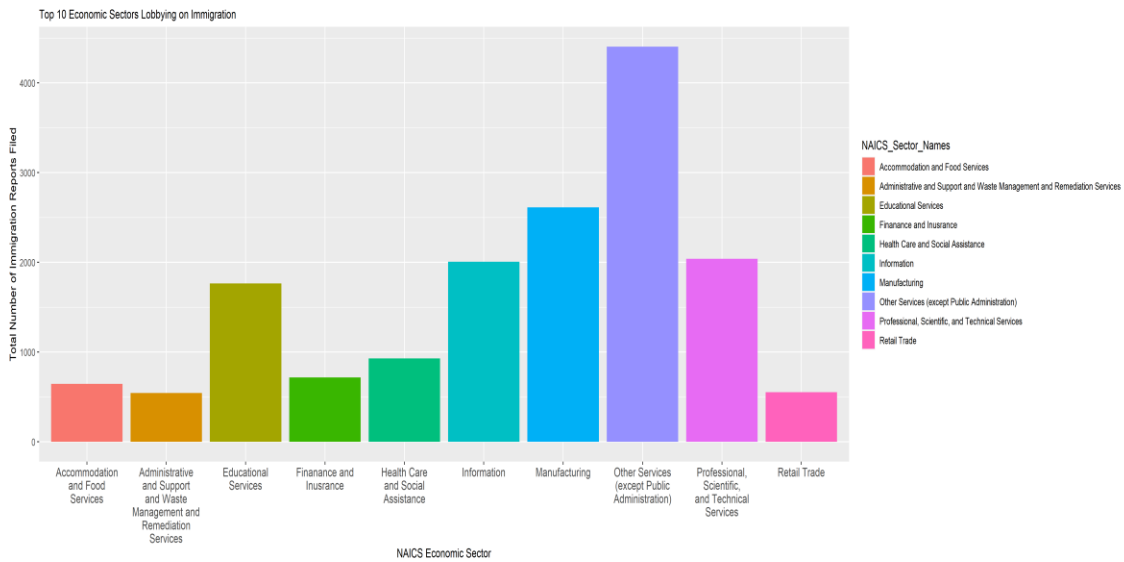
In the last twenty years, firm lobbying for immigration has been most pronounced in economic sectors like Health Care and Social Assistance and Educational Services, supporting policies that facilitate the entry of high-skilled immigration, and sectors like Agriculture, Forestry, Fishing and Hunting, and Accommodations and Food Services supporting policies that facilitate the entry of low-skilled immigration (Facchini, Mayda, and Mishra 2011). Increasingly, high-skilled foreign-born workers have concentrated in a small group of highly innovative and entrepreneurial occupations, which are closely associated with the determinants of urban growth, in STEM (science, technology, engineering, and math) occupations as well as in more interaction intensive occupations (e.g., management,

[12] Lobbyists can submit multiple lobbying reports to the Senate Office of Public Records (SOPR), expressing the lobbying preferences of their clients, however only *final reports* are considered by the SOPR for the recording of lobbying activity. For more information please see: https://www.opensecrets.org/federal-lobbying/methodology.

[13] Economic sector reflects the totality of actors within a given NAICS economic sector that listed the immigration as a lobbying issue.

finance, and economics) (Lin 2019). Additionally, low-skilled immigrants have concentrated primarily in occupations that require lower intensity of language and communication skills, but a relatively high intensity in requirement of manual and physical labor skills, often due to language and sometimes documentation status (Peri and Sparber 2009).

Figure 3-3: Top 10 Immigration Lobbying Clients (By NAICS Economic Sector)[14]



Source: https://www.lobbyview.org/data-download

What is revealing is the fact that both high-skill and low-skilled immigrant workers are imperfect substitutes of their native-born counterparts (Lewis 2013, Line 2019; Peri and Sparber 2009). This is important as it partly explains why some firms are more likely to lobby for immigration, amid a surge in their need for labor, than others. In short, firms that rely extensively on immigrant labor, are more likely to lobby for immigration than firms that rely more on native-born workers.

[14] The author of this dissertation constructed this figure using the Lobby View database (https://web.mit.edu/insong/www/pdf/lobbyview.pdf). The data for economic sectors are derived from the North American Classification System (NAICS). Per the NAICS 2017 preface, NAICS divides the economy into 20 sectors of economic activity (Executive Office of the President Office of Management and Budget 2017) (*see the research design in chapter 6 for more information)*.

3.5 Immigration Lobbying and Immigration Policy

It is worth noting that historically, immigration policy cannot be explained through lobbying alone. Often, the implementation of any new policy (immigration or otherwise) transforms the political landscape, via the creation of new political structures and institutions (like a new federal agency for example). These new institutions often produce new political *status quos*, defining and/or redefining relationships between political actors like federal and state governments, and outlining jurisdiction and power in decisions like immigration policy and its enforcement (Tichenor and Harris 2002; Zolberg 2008). In short, as E.E. Schattschneider once famously suggested, “new policies create new politics” (Schattsneider 1980).

Historically, the implementation of immigration policies—irrespective of whether they facilitate or restrict immigration—have altered and influenced developments in American politics. Thus, any discussion of new immigration policies must factor existing immigration politics, agencies, and protocols and build on them (Tichenor and Harris 2002; Zolberg 2008). Even if all firms suddenly decided they wanted to make immigration into the United States as easy as possible, no matter how much money they were to spend on lobbying, this would be insufficient to make such a radical transformation in immigration policy considering all the existing legislation and institutional players involved in immigration and enforcement in the United States.

However, even if lobbying alone does not explain immigration policy, looking at lobbying can help reveal important information regarding who the dominant actors behind lobbying are. Given the ubiquity of lobbying in American politics, immigration lobbying, may reveal the types of political outcomes firms may be at the very minimum willing to tolerate, if not actively procure. The fact that many firms tend to lobby for multiple issues at once, may very well reveal the level of acceptance they may have with respect to the *status quo* on who can enter the United States. Even if lobbying will not necessarily alter or produce legislation on immigration, it can be a strong signal of the political outcomes that firms are willing to accept.

Now that we have established the importance and centrality of lobbying, we can explore the question of technology's impact on labor. In the next chapter, by expanding on how we can conceive and theorize of the effects of technology on labor, we can then garner a better understanding of ways by which new technologies can also influence the immigration policy preferences of firms as a result.

CHAPTER 4. AUTOMATION

In this chapter, I expand on the theoretical model I use to elaborate the impact of new technology on labor. By further understanding the effects that new technologies like AI and automation have on labor, we will be able to better comprehend the ways through which automation can mediate firms' labor needs, and consequently, their immigration policy preferences. In particular, I propose that the empirical regularity assessed by Moore's Law can act as a premise for my dissertation. Namely, as new technology becomes more efficient and capable of reproducing human work, we are more likely to see technology occupy greater prominence across different economic sectors. The more technology is employed in different economic sectors, the more we can understand situations in which technology is likely to increase demand for labor, as well as when technology can contract demand for labor.

4.1 Moore's Law

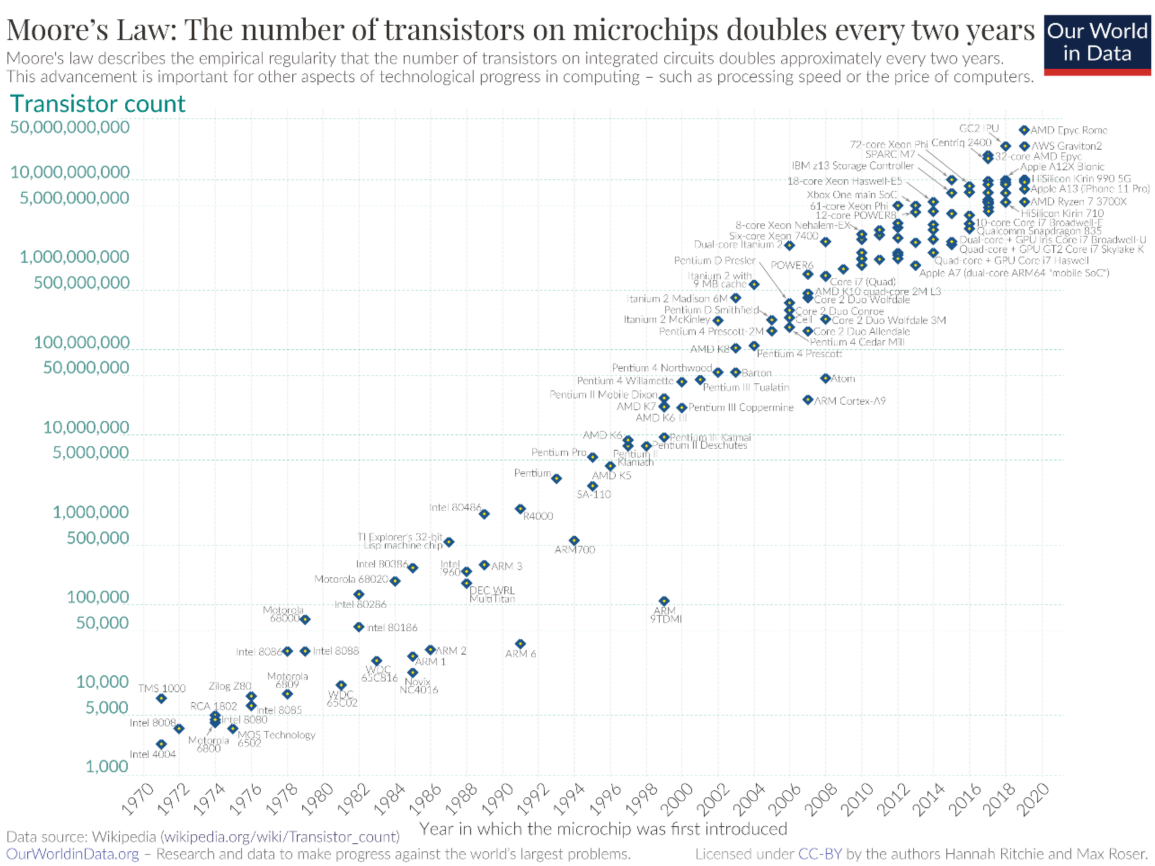
In the world of computer science there exists an important empirical observation that has assumed a degree of truism almost to the point of becoming a scientific law akin to those found in the natural sciences, called Moore's Law. Moore's Law began with a proposition made in 1965 by Gordon Moore—co-founder of Fairchild Semiconductor and Intel—who posited that the number of components per integrated circuit doubled every year (Moore 1965). Now it should be clarified that initially, Moore was referring to the number of transistors within a computer chip (Moore 1965). By 1975 Moore would revisit and revise the claim he had made a decade earlier and forecast that the rate of components per circuit board would double every two years instead of every year (Moore 1975). Since 1975, Moore's prediction has held.

The notion that the number of components per integrated circuit doubles every year or two is an important element to understanding how and why it is that computers and electronic devices more broadly, become more capable in the reproduction of tasks. To understand the link between computers' potency and the number of transistors we need to understand the following. Computers, along with other electronic devices from cell phones to toy musical organs, essentially perform a series of functions and actions, like representing and processing data in the case of a computer, to reproducing musical sounds and keys in the case of toy organs. Moreover, we can also think of these electronic devices as the sum of their parts, wherein the parts of these devices themselves perform certain tasks which enable a device like a computer to represent and process data.

Computers, for example, contain computer chips, chips contain modules, modules contain logic gates, and logic gates contain transistors. We can think of transistors as a type of switch, similar to the light switch we use to put on or off the light in a room (Roland 2016, 7). When we press the on button, we are essentially allowing the flow of electric current to a lightbulb, and when we press the off button, we are restricting the flow of current to the lightbulb. In the context of electronic devices, transistors essentially can control the flow of current from one part of a chip to another. This is important, as electronics (as the name suggests) are devices that function by controlling the flow of electricity through their parts. Transistors can also act as amplifiers (Roland 2016, 5), or current boosters, much like a microphone amplifies one's voice. A good example of a transistor acting as an amplifier is a hearing aid, which picks up sound waves, which are amplified through a transistor within the device (i.e., the hearing aid).

Since transistors can open or block the flow of electricity, having more transistors per computer chip permits for more logic gates, which in turn permits for electronic systems like computers to perform more functions (Borkar and Chien 2011). Thus, what Moore's Law elucidates is that smaller transistors enable computer chips to have more transistors per unit. The more transistors there are, the faster and more efficiently they can move electricity along the circuit (After Moore's law | Technology Quarterly n.d.). The faster and more efficient electricity can flow, the more efficient the computer becomes at performing tasks like representing and processing data (After Moore's law | Technology Quarterly n.d.). As Figure 4-1 shows, we can see that between 1970 and 2020 there was an exponential rise in the number of transistors within microchips of almost one billion percent.

Figure 4-1: Moore's Law



4.1.1 Why Moore's Law Matters

By looking at Moore's Law we can see that as computers become more powerful and efficient, they also become relatively more economical cheaper (Markoff 2015). While smaller does not mean inexpensive, comparatively speaking, the smaller and more efficient transistors are, the cheaper they become, compared to previous less efficient models. For example, a computer chip that contained 2000 transistors in 1970 would cost $1,000 (Lynch, Smith, and Howrath 2016). By 1972 the cost of a computer chip was equal to $500, $250 in 1974, about $0.97 in 1990 and close to $0.02 in 2016 (Lynch, Smith, and Howrath 2016).[15]

From 1975 until 2020, computers and other electronic devices have consistently become more powerful and efficient in the reproduction of tasks, and they became comparatively cheaper. As computers and other electronic devices become cheaper and more efficient at reproducing tasks, the more they are utilized by different actors from different economic sectors in the assistance of work.

4.1.2 Limits to Moore's Law

It is important to note that while Moore's Law has since 1975 been accurate in its predictions, many computer scientists, including Gordon Moore himself, have spoken about the limits of Moore's Law (Guardian 2020). Firstly, there are physical limits to how small a transistor can get. For example, the first transistor, built in 1907, measured about 10 millimeters (mm). In 1947, a transistor could measure 40 micrometers (for context, there are 1000 micrometers in 1 millimeter). By 1971, transistors could measure as little as 10 micrometers. And by 2017, transistors could be as small as 14 nanometers (there are 1000 nanometers in 1 micrometer) (Hazari 2017). To put this into context, a transistor in 2017 was

[15] The notion that computers would get cheaper and more powerful is referred to as Moore's Second Law (Lynch, Smith, and Howrath 2016).

almost 8 times smaller than an average HIV virus, and only about 14 times wider than DNA molecules (Hazari 2017). Given current understanding of physics and quantum mechanics, it is highly unlikely, if not highly improbable, for the current rate of transistor shrinkage to continue (Hazari 2017). There could very well be a physical limit to how small such things can be built.

But, even if there is a limit as to how small transistors can be built, transistors may have already reached a limit in their size on the basis of functionality. As transistors get smaller, they become less effective in controlling the flow of electrons (Waldrop 2016). It is believed that a transistor smaller than 5 nanometers loses its ability to control the flow of electrons as the electrons will be able to pass through the transistors through a phenomenon known as quantum tunneling (Sperling 2018). If a transistor can no longer control the flow of electrons, it loses its ability to regulate the flow of electricity, and thus its functionality within chips.

The question then is, if we do see an end to Moore's Law can we therefore presume a limit to the types of tasks that computers or other machines will be able to replicate? If the answer is yes, then this would mean that what differentiates routine from non-routine tasks would eventually become constant, i.e., there may be a limit as to the types of tasks that can be made routine with respect to machines. If the answer is no, i.e., the processing power of computers and other electronic devices continues to grow exponentially, then this means that the nature of what makes a task routine versus what makes a task non-routine is mutable and therefore malleable.

Although the fate of computer processors, microchips, and transistors is uncertain, alternative forms to standard computing technology such as quantum computing or artificial intelligence stand out as likely alternatives to reliance on transistors, which are likely to make computers and electronics even more powerful in the replication of tasks. Unlike standard computers, which rely on transistors which are combined to create logic gates, which in turn create information via regulating the flow of electrons; quantum computers exploit elements of quantum mechanics like quantum super positioning[16] and quantum entanglement[17] (Highfield 2018). Moreover, advances in artificial intelligence (AI) show that computing power can be enhanced without having to recur to newer or smaller computer hardware. At its core, AI relies on algorithms. An algorithm is a series of well-defined computer implemented instructions, designed to solve a specific set of computable problems (The Definitive Glossary of Higher Math Jargon | Math Vault 2019). In essence AI, merely enhances and/or introduces new algorithms to existing computers that can improve, enhance, and even enable new functions for existing computers, to the point that new algorithms can even improve the performance of older computers (Puiu 2019).

For the purpose of this dissertation therefore, based on Moore's Law, we can assert as an empirical regularity the notion that computers have not only gotten more powerful, efficient, and cheaper with time, and that in so doing, they have assumed a degree of ubiquity across economic sectors to perform numerous tasks. Lastly, given developments in AI and quantum computing, it stands that there may likely be a continuation in the growth of tasks and capabilities that newer computers and electronics will be capable of reproducing.

[16] From the perspective of quantum physics, superpositioning asserts subatomic particles can assume different configurations or arrangements at the same time (Dirac 2019)
[17] Occurs when a pair of particles are generated in such a way that the individual quantum states of each particle are indefinite until they are measured (Dirac 2019).

4.2. What Is in a Word?

Now that we have understood how and why we are more likely to witness the diffusion of electronics and other technologies across economic sectors, it is worth turning our attention to the interplay between technology and work, namely in the form of automation. Although the word automation may invoke the prospect of advanced machinery, like robots, or complex systems like artificial intelligence (AI), as a concept the word automation dates even before the Industrial Revolution. From the etymological roots of the word, we can see that *automation*[18] literally means the development of a self-propelling entity or mechanism (Marshall 1957, 150). Prior to the Industrial Revolution, *automation* existed as a concept that laid at the intersection of theology, philosophy, and the natural sciences, wherein it served primarily to describe the relationship between God and different phenomenological entities. To put it differently, something like the universe or even the human organism could be thought of as types of *automation* (Marshall 1957, 150). We also witness reference to the use of *automation* in the description of machines. For example, Thomas Hobbes refers to *automata* as engines that could move themselves by springs and wheels, like a watch for example (Hobbes 1994, 3).

However, it is not until 1948 that the word *automation* begins to be referenced as a substitute of labor. Seemingly inadvertently, the first reference of the word automation being used in the context of labor, occurred when then Ford's Vice-President Delmar S. Harder, allegedly stated that, "What we need is more automation" in reference to devising more efficient and effective ways to handle and transfer of parts between successive production

[18] The word automation is composed by the Greek roots, *auto* (self) and *matos* (to think), plus the Latin suffix *ionem,* often used to transform a verb into a noun ((-ion | Origin and meaning of suffix -*ion* by Online Etymology Dictionary n.d.).

operations in the assembly of automobiles (Marshall 1957, 149). While Harder was referencing *automation* strictly in the context of automobile assembly, the term quickly spread and was adopted by different social actors, including economists, industrialists, and labor leaders (Marshall 1957).

Perhaps unintentionally, the novelty and value of Harder's neologism provided a new way to vocalize existing apprehension and fear regarding technology. Although automation could innovate and improve production, it could also undermine human labor and the welfare of many workers. Contrary to the technological optimism articulated by figures like Francis Bacon, for example (Bacon 1915), the term *automation* could be used to suggest the more destructive social effects of technology (Fairless 1955; Rifkin 1995). In short, post Harder, *automation* became both a noun (explaining the process in which machines could replicate and replace human labor) but also a verb (as in to automate, meaning the transformation of human activities, into activities operated by machines) (Marshall 1957, 149).

The fear of technology causing more harm than good was also not necessarily something that started with the Industrial Revolution. Already in the Platonic dialogues *Timeaus* and *Critias,* for example, the myth of Atlantis is used to illustrate the dangers that could be incurred by a society that becomes technologically hubristic. In the myth, we learn that Atlantis was once a great, prosperous, advanced, and virtuous society that ended up degenerating into a licentious nation, one where technology furthered greed and corruption. As punishment for Atlantis's degeneracy into vice, in part furthered by technology, the gods ultimately destroyed and sunk the city to the bottom of the ocean (Plato 2008).

However, since the industrial revolution, the fears of technology often centered around the prospect of a technologically induced poverty. While the myth of Atlantis cautions about how technology can take humans down the path of indolence and vice, something for which there is certainly grounds to ponder and worry in today's context, much of the concerns regarding technology in the aftermath of the industrial revolution revolve around the prospect of technologically induced unemployment and unemployability.

One of the most memorable historical instances in which societal actors denounced, both in word and deed, the impact that technology was having on labor was the Luddite Rebellions in 19th century Britain (Conniff 2011). The Luddites, who were essentially a group of artisans and craftsmen, began protesting the growing presence and reliance of factories and machinery in Northern England for the production of textiles. For the Luddites, machines were not only replacing them in the production of textiles, but they were also rendering them unemployable as their skills became increasingly incompatible with the new types of mechanical mass production. In protest, the Luddites would often take over factories and destroy the machines (Linton 1992).

While the anxiety over the growing presence of machinery did not always end in dramatic episodes such as the Luddite Rebellions, even among some of the more optimistic enthusiasts of industrialism and capitalism we can also see apprehension about the potential risks involving the impact of technology on labor. David Ricardo, for example, suggested that labor saving technology could reduce the demand for undifferentiated labor, generally low-skilled and lower-income, thereby creating a condition of technological unemployment (Ricardo 2016). Similarly, John Maynard Keynes predicted that while new technology could increase per capita income, it also had the capacity to eventually generate widespread unemployment once machines became more sophisticated, rendering labor redundant (Keynes 2010). Likewise, the Russian American economist Wassily Leontief famously suggested that new technology would be for workers what tractors and automobiles had been for horses (Leontief 1982).

4.3 Labor as a Series of Tasks

While new machinery may have contributed to the demise of artisans and other medieval guilds, new machines also enabled the creation of textile mills and factories in the 19^{th} century, generating demand for new types of work. For example, the machines that displaced the Luddites were ultimately built, operated, repaired, and cleaned by other workers. In essence, as new machinery rendered certain occupations redundant, they also generated demand for human labor for other occupations, sometimes even creating entirely new occupations that did not exist before (Acemoglu and Restrepo 2019a, 4).

Thus, in looking at tasks, we are more likely to assess how technology impacts labor (Acemoglu and Restrepo 2019; Autor, Levy, and Murnane 2003). Instead of regarding *automation* as a "black box model,"[19] (i.e., as a process in which we know little about how or why it is that machines affect labor) by looking at labor as a collection of tasks enables us to better understand the necessary conditions in which technology can displace labor, as well as when technology can complement or even generate new demand for labor (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Autor, Dorn, Hanson 2015; Autor and Dorn 2013; Dao et al. 2019; Frey and Osborne 2017).

[19] The term "black box model" draws attention to the observation of a system or organism, where inputs to and outputs from the system or organism are observed and known, yet little is known about the how those inputs are turned into output. In essence, a "black box model" is illustrative of instances in which a relationship is asserted between two variables but where there is insufficient information or knowledge about how one variable affects the other (Singleton and Straits 2010, 476).

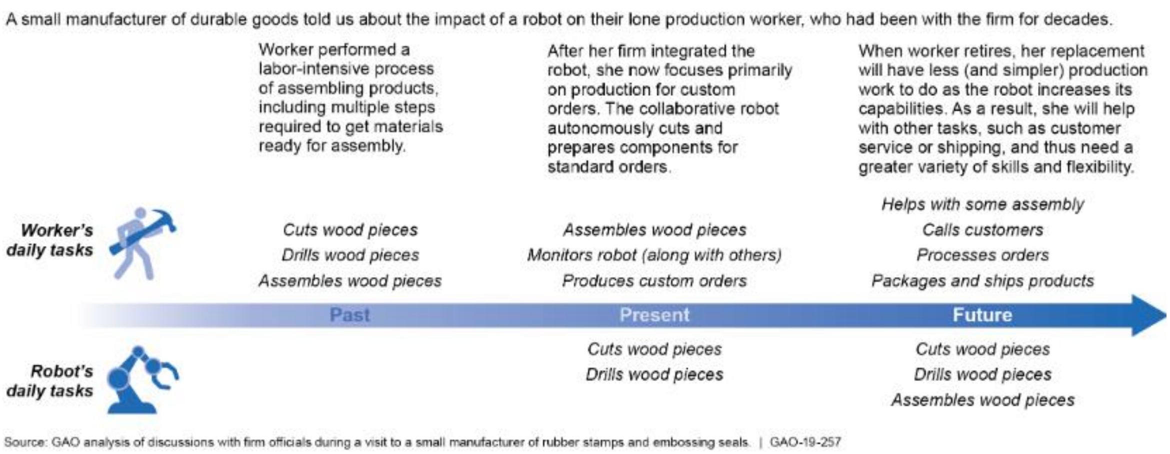
4.3.1 The Displacement Effect

When machines become more productive in the execution and reproduction of a task or tasks, and subsequently when machines become economically accessible for employers, this in turn will lead to a decrease in the reliance on labor and an increase in the usage of machinery in the reproduction of the corresponding task(s). Engineering machinery to replicate labor in the performance of tasks has been ongoing since the Industrial Revolution. Initially, machines were built to primarily reproduce physical tasks, for example movement, lifting, or digging through soil. However, amid the development of newer technology like computers, we begin to see how manufactured machines can reproduce physical, but also increasingly cognitive tasks (Autor, Dorn, Hanson 2015; Frey and Osborne 2017). AI-powered technology along with developments in robotics have extended the list of tasks that machine hardware or software can do, like preparing taxes, translating written documents, preparing legal briefs, and even diagnosing diseases (Acemoglu and Restrepo 2018, Acemoglu and Restrepo 2019a; Acemoglu and Restrepo 2020; Acemoglu and Autor 2010; Autor, Dorn, Hanson 2015; Frey and Osborne 2017).

Acemoglu and Restrepo (2020) refer to the *displacement effect* of automation on labor, instances in which: a) it is possible for machines to replicate human labor in the reproduction of tasks and b) it is less costly and more efficient to rely on machines for the reproduction of task(s) than human labor. It is this *displacement effect*, featuring machines replicating and reproducing tasks more efficiently and effectively than labor, which in turn yields a replacement of labor by machines (Autor, Levy, and Murnane 2003; Autor, Dorn, Hanson 2015; Frey and Osborne 2017). In short, technology is more likely to displace labor, when the latter is performing routine tasks, i.e., tasks that require the "methodical repetition of unwavering procedure, they can be exhaustively specified with programed instructions and performed by machines" (Autor, Levy, and Murnane 2003, 1283).

Figure 4-2, in part, summarizes this logic. We can appreciate that initially there is human activity involving the completion of a series of tasks. Eventually though, some of these tasks can be reproduced by machines, replacing workers from this activity. For example, in Figure 4-2 we can see how the activity of cutting wood pieces was initially performed by workers, but subsequently by robots.

Figure 4-2: Illustration of Changes to a Worker's Tasks after a Selected Firm Integrated Collaborative Robot.



4.3.2 Complementary Effect

While new technology has the capacity to replace labor in the reproduction of tasks, this does not mean that new technology, by virtue of being new, is *ipso facto* an alternative to human labor. Historically, new technology has also helped generate employment opportunities for existing labor. For example, the introduction of automated teller machines (ATMs), rather than reducing or eliminating demand for bank tellers actually increased it (Bessen 2015). This was because ATMs reduced the costs of operating a bank branch, thereby permitting banks to open more branches geographically (Bessen 2015). The more branches banks opened geographically, the more they required the services of, and thus employed, additional bank tellers.

Thus, even if ATMs were more efficient in the reproduction of tasks like counting and dispensing cash for clients, ATMs also permitted bank tellers to assume new functions as employees. As ATMs took over dispensing and depositing cash into bank accounts, banks began to broaden the range of tasks/responsibilities for their human tellers (Autor 2015). Because of ATMs, human bank tellers went from being primarily check-out clerks, to sales-representatives working for banks, who could establish or deepen customer-bank relationships, by promoting or offering additional bank services like credit cards, loans, and investment products (Autor 2015; Bessen 2015).

This *complementary effect* of automation on labor (instances in which automation is likely to deepen demand for labor for existing occupations) is more likely to occur in situations in which the automation of one task generates demand for ancillary tasks. In the case of ATMs, the automation of bank-telling, "liberated" human tellers from primarily helping clients access their bank accounts and permitted them to do other tasks and functions for the bank. In many ways, the complementary effect is more likely to favor individuals possessing skills compatible to those ancillary tasks (e.g., human bank tellers became more like sales and public relations representatives to the bank than mere accountants). Moreover, we are more likely to have the complementary effect in instances in which demand for a good or services steadily increases.

4.3.3 The Additive Effect

Historically though, any initial benefits incurred by the *complementary* effect of automation, tend to be limited and eventually overturned by the *displacement* effect. On the one hand, as discussed above, if the automation of one or multiple tasks inherent to the production of a good or service helps increase consumption, then it is possible that demand for ancillary tasks also grows, especially as consumption of the good or service grows. On the other hand, eventual developments in technology may further the number and nature of tasks that machines can reproduce more efficiently and effectively than labor, subsequently permitting newer technology to displace labor from even more occupations.

In the abovementioned case of banking, while ATMs may have initially allowed banks to open up more physical branches, thereby employing more human tellers, developments in online banking technology have increasingly allowed bank clients to meet many of their banking needs without having to be physically present inside any of their bank branches. In fact, online banking permits clients to make payments for many goods or services without needing to rely on cash. Thus, even if there were gains incurred for labor through the *complementary* effect, in the long term it becomes possible to further automate and thereby displace labor from more and more tasks. While banks may still employ people to provide services for customers it is likely that any initial benefits incurred by ATMs have been offset through other forms of automated banking (putting aside the impact that the 2020 pandemic may have had to in-person services like banking).

Historically, what has really helped offset the displacement effect of technology on labor has been situations in which new technology creates entirely *new tasks*, and even entirely new economic sectors, for labor. We can think of these situations as reflective of the *additive effect*, where new technology enables the development of entirely new tasks that employ labor. Consider the example of the railroad. Though the railroad may have decimated demand for the stagecoach and the pony express as modes of transporting people and cargo across the United States, it also introduced a plethora of new tasks, that did not exist prior to its invention, which in turn employed labor (for example, machinists, engineers, cleaners, repairers, ticket-sales people, and more). More recently, it is estimated that between 1980 and 2010, developments in automated technologies both created new and expanded the range of job titles through the *additive* effect, which accounted for half of employment growth during this same time period (Acemoglu and Restrepo 2018). For example, careers in genetic counsellor, content moderation in social media platforms, and web developers, stand out as occupations, which were non-existent before the 1990s, but currently employ numerous people in different countries around the world.

In spite of the growing complexity and capability of machinery to replicate human tasks, human beings tend to be more adaptable to new situations and are generally more amenable to perform work in new tasks than machines are (Acemoglu and Restrepo 2018). Thus, as new technology replaces labor in the reproduction of certain tasks, human beings can capitalize on new opportunities to perform work, as a direct or indirect result of new technology.

Furthermore, from a sequential point of view, in order to produce machines that replicate labor activity, it is necessary that labor as an activity precedes the introduction of technology to reproduce work. Engineers and programmers may be able to build or program devices that replicate human work, but those engineers and programmers must first understand the actions that workers are doing in the first place and determine whether it is possible for machines to execute the reproduction of tasks performed by workers (MacKenzie 1984). In short, labor is implicit to machinery and technology, in that not only are workers the ones who build or program machines, but also these machines are ultimately built for, or programmed, to replicate activity that is performed by workers (Marx 1990).

Thus, new technology opens up opportunities for labor associated in the production of the new technology. Whether it is engineers making micro-processors used in computers, or programmers who can moderate content in social media platforms, until the activities of those workers are fully engineered into other machines, it is likely that it will be human workers who perform those tasks. This in turn means that sometimes it is a question of understanding, costs, or logistics that explains why some occupations are not immediately automated, and thereby displace workers. Especially in the context of creating new technology, or in dealing with occupations created by new technology, engineers and programmers may lack the knowledge, or resources or both to render machinery able to reproduce human work. Moreover, until programmers and engineers fully understand or have at their disposal the means to program machines to replicate certain tasks, human beings will continue to be relied upon.

Consequently, whether we are dealing with the *complementary* or *additive* effect, new technology is more likely to complement or even generate demand for new labor that is performing non-routine tasks. In other words, when labor engages in activity in which the rules [to perform a given task] are not sufficiently well understood to be specified by computer code and executed by machines (Autor, Levy, and Murnane 2003, 1283). By extension, the skills necessary to perform routine tasks can also be routine, while those needed for non-routine tasks could be non-routine skills. If we refer back to Figure 4-2, we can see that although machines can now perform more tasks like cutting, drilling, and assembling wood, thereby displacing workers, human workers are able to render their services in other capacities like helping with assembly, calling customers, and processing orders.

4.4 Types of tasks

According to this logic, cognitive and manual tasks can be both routine and non-routine. For example, record-keeping is a task that requires cognitive yet routine skills, while occupations that require forms of deductive or inductive reasoning compiled with being an effective and persuasive communicator entail non-routine skills (Autor 2015). Similarly, manual tasks like sorting clothes exemplify routine labor, while cleaning and janitorial work are inherently non-routine, since workers must be able to exert physical work but also delegate, negotiate, and supervise the work of others, making it very difficult for a machine to be adept to reproduce all of these tasks (Autor 2015).

Table 4-1: Summary of features of Industry Occupation Categories

Features	**Non-Routine Manual Intensive Occupations**	**Routine Occupations**	**Non-Routine Analytical Occupations**
Education level	High-School Diploma or less	More than a high-school diploma but not a professional degree, or a bachelor’s or higher	A bachelor’s degree or higher
Nature of work	Perform heavy physical work, possess a degree of physical dexterity, and/or flexible interpersonal communication	Labor is procedural, well-defined, and more likely to be substitutable by machinery	Abstract, analytical, cognitively complex problem-solving, and coordination work
Income level	Low-income occupations	Middle-income occupations	High-income occupations
Examples	Cooking, housekeeping, baby-sitting, health care, food, and landscaping	Typists, production worker, travel agent.	Doctors, lawyers, Engineers, computer programmers and software engineering

The more complex technology becomes the more tasks it can replicate. In this sense, there is a new horizon in terms of the types of human activities that technologies like artificial intelligence (AI), robotics, and computer algorithms, can replicate and therefore are more susceptible to displacement (Frey and Osborne 2017). For example, until recently driving a vehicle (e.g., car, bus, or truck) was conceived as a non-routine task, given the need to combine cognitive and physical elements to execute the task (i.e., to drive), yet recent developments in computer technology have produced driverless vehicles (Frey and Osborne 2017).

Table 4-1 summarizes important features of routine and non-routine occupations, ranging from the education level often associated with each type of occupation, to the nature of work and income level associated with routine and non-routine occupations. What is significant when looking at Table 4-1, is that we see how there are non-routine occupations that are both physically intensive as well as more analytically intensive. This is significant, because in looking at the examples featured in Table 4-1, we can see that low-skilled occupations, like cooking and baby-sitting, can be non-routine, in the same way that high-skill occupations like engineering are also non-routine. By contrast, and seemingly counter-intuitive, we see that occupations like telemarketers and customer representatives may be more routine, despite requiring higher skills from their workers than say housekeeping.

4.5 A Complicated Relationship

Even if automation does not necessarily culminate in human obsolescence, new technologies may often alter opportunities of employment in ways that are neither painless nor benign for workers. For one, as seen with the Luddites, new technology can render certain types of work and workers obsolete, as their skills (of the displaced workers) become increasingly incompatible with the new types of work made available by new machinery. Thus, displaced workers are sometimes confronted with the prospect of either acquiring new skills—which often entails education or apprenticeship—or risk becoming unemployable, given the new types of labor demand.

Second, even when new technologies generate new tasks that demand and employ labor, these types of new work may downgrade workers in terms of skill-input and economic compensation. New technology can *deskill* labor, by introducing new tasks for labor that limit rather than expand the skill-input necessary from workers to perform the given task. Thus, new technology may provide employment opportunities for many workers in occupations that are comparatively low paying and vocationally unfulfilling (James and Skinner 1985; Goldin and Katz 1998). Adam Smith long ago warned in the *Wealth of Nations* how new machinery could create occupations that were repetitive, tedious, and demanded little intellectual input from workers, taking a toll on the mental and physical health of workers (Smith 1979, 781-782).[20] Similarly, Karl Marx pointed out that the introduction of machinery, rather than eliminating labor, furthered the division of tasks, often rendering the nature of the work redundant, tedious, and exploitative (Marx 1978, 216). The more *deskilled* labor becomes the more its share in income contracts, i.e., the more basic the tasks labor is

[20] Smith stated that, "The man whose whole life is spent in performing a few simple operations, of which the effects are perhaps always the same, or very nearly the same, has no occasion to exert his understanding or to exercise his invention in finding out expedients for removing difficulties which never occur. He naturally loses, therefore, the habit of such exertion, and generally becomes as stupid and ignorant as it is possible for a human creature to become. The torpor of his mind renders him not only incapable of relishing or bearing a part in any rational conversation, but of conceiving any generous, noble, or tender sentiment, and consequently of forming any just judgement concerning many even of the ordinary duties of private life... His dexterity at his own particular trade seems, in this manner, to be acquired at the expense of his own intellectual, social, and marital virtues. But in every improved and civilized society, this is the state into which the labouring poor, that is, the great body of the people, must necessarily fall unless the government takes some pains to prevent it" (Smith 1979, 781-782).

required to do in terms of skill-input, the lower its relative compensation (Autor and Dorn 2013).

New technology then, can increase productivity and maximize labor efficiency, while causing worker compensation to stagnate, especially when automation *deskills* labor (Marx 1978, 216). In the last three decades, for example, automation has contributed to the bifurcation of the workforce in advanced economies like the United States. On the one hand, automation has generated demand for high-skilled workers who can adapt to the exigencies of new and more sophisticated forms of capital (Autor and Dorn 2013; Basso, Peri, and Rahman 2020). On the other hand, given its ability to *deskill* work, automation has also contributed to the rise in work opportunities that are generally underpaying (Autor and Dorn 2013). It is worth noting that since the 1970s although the productivity of labor has increased globally, there has been a contraction in labor's share of income. In essence, as worker productivity has steadily increased, the relative compensation of workers has stagnated (Acemoglu and Restrepo 2018; Acemoglu and Restrepo 2019; Dao, Das, and Koczan 2019; Frey and Osborne 2017; Karabarbounis and Neiman 2014).

While this decline in labor's share of income has been exacerbated by numerous factors including trade and firm mobility, especially in developed economies, automation has aggravated income inequalities (Autor and Dorn 2013; Basso, Peri, and Rahman 2020).Therefore, even when automation helps to generate demand for labor, it can also further income inequalities (Acemoglu and Autor 2010; Autor, Dorn, Hanson 2015; Dao, Das, and Koczan 2019; Goos and Maning 2007; Goos, Manning, and Salomons 2014).

Hence, the challenge which lies ahead regarding automation is the extent and degree to which governments will tolerate the rising bifurcation and polarization of labor. It becomes important, then, to not only identify where the new opportunities for labor lie, but also to ensure that labor can transition into new occupations without necessarily being *deskilled,* therefore undercompensated. In the end, the biggest challenge for labor is not the prospect of technological determinism (i.e., that technology dictates the societal structures of any given epoch). Instead, the biggest challenges to labor stem from political and business decisions that are neither inevitable nor irreversible. For example, in the United States the existing tax code subsidizes the use of machinery and other types of equipment, yet taxes the employment of labor (e.g., payroll tax) (Acemoglu and Restrepo 2019a), which in turn encourages business to rely and invest more on technology over human capital (Acemoglu and Restrepo 2019a).

So far, we have seen how new technologies have multiple effects on labor. However, what is missing for our research is what would propel firms to lobby on immigration in the first place, especially in the face of growing automation and the fears that it may further induce technological unemployment (Geiger 2018). Even if automation is not entirely displacing labor all together, the question remains, under what conditions would it increase demand for labor and thereby prompt firms to lobby more favorably for immigration. In the next chapter I will discuss how, looking at tasks, we may get a clearers sense on the ways automation may at times increase demand for labor, and subsequently immigration lobbying.

CHAPTER 5. THEORY

In this chapter, I outline the logic of my theoretical argument. I expand on the logic of task-based models, which posit that by understanding labor as activity consisting of the completion of a series of tasks, permits a more nuanced account regarding how and when technology can undermine labor, but also complement it. Building on the relationship between technology and labor, and my prior discussion on lobbying (see Chapter 3), I will then articulate the logic of my argument for this project. In particular, how we can use an account of a task-based model, to not only understand ways by which automation can increase demand for labor but also, as I propose, firm lobbying for immigration, as a way to meet firms' production needs. I will conclude this chapter by articulating my hypotheses and some potential limitations inherent to this project.

5.1 The Complexity of Measuring Political Lobbying

In accordance to the Lobbying Disclosure Act (LDA) of 1995, and the sube.g.,ent Honest Leadership and Open Government Act of 2007, lobbyists are required to submit a lobbying report to the Senate Office of Public Records. This report should indicate their client (e.g. lobbyist x could be lobbying on behalf of company Y), the political issues being lobbied on (see Appendix Table A-2 for a complete list of the current political issues actors can lobby on) and the amount being spent on lobbying. Although lobbyists are required by law to list: a) the name of their clients, b) the political issues being lobbied on, and c) the amount being spent on lobbying, this does not necessarily reveal how much is being spent lobbying per political issue. This is because lobbyists can itemize the political issues they are lobbying on in a single report, and list the total lobbying amount as an aggregate sum.[21]

[21] Lobbyists must file a separate report for each individual client (Delmas, Lin, and Narin-Brich 2016, 195).

For example, company *X* could hire lobbyists *Y* in year *ZZZZ* and spend one million dollars lobbying on political issues like immigration, trade, and taxes. While the lobbying report in this hypothetical example would indicate that on year *ZZZZ*, company *X* hired lobbyist *Y* and spent one million dollars lobbying, lobbyist *Y* is not required to list how much money company *X* is spending per issue. Thus, we may find a reference that in year *ZZZZ,* company *X* lobbied on immigration and spent one million dollars. However, if company *X* also lobbied on taxes and trade, we cannot determine what percentage of the million dollars was devoted to each issue. (Brulle 2018, Delmas, Lin, and Nairn-Brich 2016).

Consequently, when looking at lobbying reports we must consider two things. First, we can say that any time immigration is listed in a lobbying report, whatever the amount associated in the report was, represents the cost that a given firm was willing to incur to include political issues like immigration. In short, if company X spent one million dollars and listed immigration among its political issues, we can assume that company X was willing to incur this cost for political objectives, including ones related to immigration. Second, we can look at the number of reports that list immigration as a lobbying issue. By counting the number of reports that list immigration, we may get a sense of variation from year to year with respect to immigration lobbying. This will allow us to ascertain when there are increases and decreases in immigration lobbying (which is essential if we are trying to explain immigration lobbying as an outcome of automation's effects on labor).

When parsing through the lobbying data, it is common to find multiple copies of the same lobbying report in any given year, as clients may ask lobbyists to amend their lobbying report. For example, clients may change the amount being dispensed to lobby for an issue(s) and/or modify the issue being sought after, or the lobbyist can also report intention to lobby without necessarily doing so (i.e., lobbying) at the time of filling the report. We can think of this process as the difference between a lobbying report that acts like a draft versus the final lobbying report submitted. Thus, in addition to looking lobbying reports that list immigration as a lobbying issue, we must ensure to look only at the finalized reports, as the definitive amount worth considering for my any analysis.

One caveat we must keep in mind, though, is that even if looking at annual reports may be useful in gauging variation in immigration lobbying, we cannot conclude that this is indicative of variation in lobbying in support of policies that facilitate immigration to the United States. Although lobbyists must list the political issue they are lobbying for on behalf of their clients, the report does not oblige lobbyists, or clients, to disclose whether they are lobbying *favorably* or *unfavorably* on an issue. In other words, actors who seek policies that facilitate the entry of foreigners, as well as actors desiring to limit or halt the entry of foreigners, would list immigration as the issue they are lobbying.. Therefore, just because an actor lists immigration as a lobbying issue, does not mean that the actor in question is supportive of policies facilitating immigration. As we can see in Appendix Table A-1, for example, one of the more prominent organizations that lobbied on immigration between 1999 and 2017 was NumbersUSA, an anti-immigration advocacy organization whose aim is to "reduce legal and illegal immigration" (De Parle 2011).

In addition to looking at reports that list immigration as the issue being lobbied, it is also important to search for key words under the "Specific Issues" section of the Center for Responsive Politics (CRP) lobbying data or the reference to a congressional bill. In some reports (though unfortunately not in all), in addition to listing the issue being lobbied on (e.g., immigration) lobbyists also included a description of the policy outcomes being sought. For example, in addition to listing immigration as the issue being lobbied, some reports also specify a particular bill's name (or number). Therefore, by looking at reports that list immigration as an issue being lobbied on and include a description of what it was about immigration that the client was lobbying for, the data is useful to assess which actors lobbied favorably for immigration outcomes and which actors were not.

However, even when immigration lobbying reports specified the immigration-related issue being sought, reports tended to be inconsistent in their use of spelling, capitalization, and punctuation, very often featuring short, poorly structured text descriptions (Liao et al. 2015). Thus, we end up with reports in which the same political issue or objective is listed, albeit written differently, e.g., Immigration Reform vs immigration reform,[22] or h-2b vs H2b vs H2-B[23].[24] This can be problematic when doing any type of data analysis, as reports with different spelling (e.g., h-2b vs H2b vs H2-B) could be counted separately by statistical software programs.[25] To avoid confusion, I opted to look at the recurrence of individual key words within those listed under Specific Issues of immigration lobbying reports.

Figure 5-1 summarizes the top five recurrent words listed in immigration lobbying reports. To some extent, we see that words like act, immigration, issues, and reform are not very revealing of anything and most likely might been used in conjunction to describe something else like immigration reform or immigration act. However, the word 'visas' is

[22] In the context of the United States, immigration reform can be thought as a "catchall" expressing the desire to change existing laws governing immigration. More often, the term is used by those who advocate a path to legal status for undocumented persons in the United States. However, the term has increasingly been used by those who seek more restrictive immigration laws and enforcement (Gamboa 2018).

[23] The H-2B Visa is intended for employers to hire foreign worker to come temporarily to the United States to perform temporary non-agricultural services or for work that is on a one-time basis, seasonal, peak load, or intermittent (H-2B Temporary Non-Agricultural Workers | USCIS 2021).

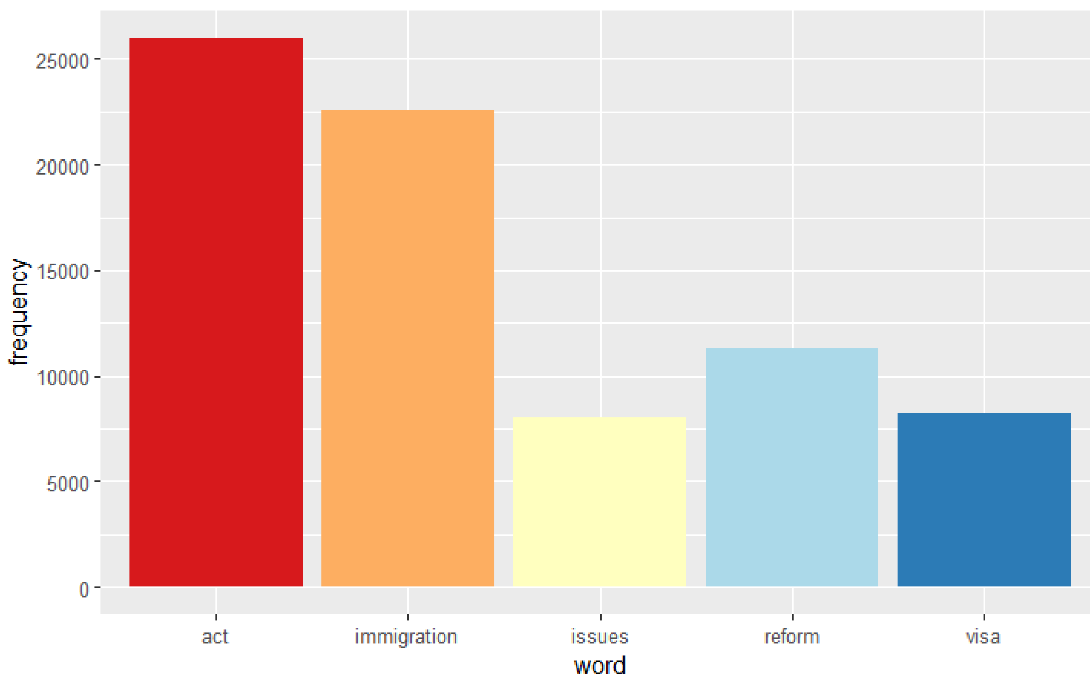
[24] For Table A, I made sure to standardize differences in the capitalization of words, so as to not have the previous example of Immigration Reform and immigration reform being counted as separate specific issues. Yet, we still have lobbyists referring to the H-2B visas in three distinct manners, for example.

[25] All my data analysis was conducted using RStudio.

indicative as questions of visas pertain to more specific outcomes involving the permissible entrance into the United States by foreign-born individuals.

A closer look at figure 5-2 now shows the 50 most recurrent words associated with immigration lobbying reports. We see that among the more common themes behind immigration lobbying are questions involving workers, visas, and economics. In short, among the most recurrent policy objectives, we see a considerable recurrence among actors lobbying on immigration that consider questions of production and labor needs among immigration lobbying reports.

Figure 5-1: Top Immigration Lobbying Key Words



Source: https://www.opensecrets.org/bulk-data

Figure 5-3 consists of the largest lobbying clients who listed immigration as a lobbying issue between 2009 and 2021 and spent at least 1 million dollars in lobbyin. The vertices (or lines) represent the number of bills which these firms lobbied for (more strings between the nodes, means more bills). For example, in figure 5-3 we see that the company

Verizon is associated with only one vertex while a company like General Motors is associated with two, i.e., Verizon is associated with having listed one bill in its lobbying reports while General Motors is associated with two bills.

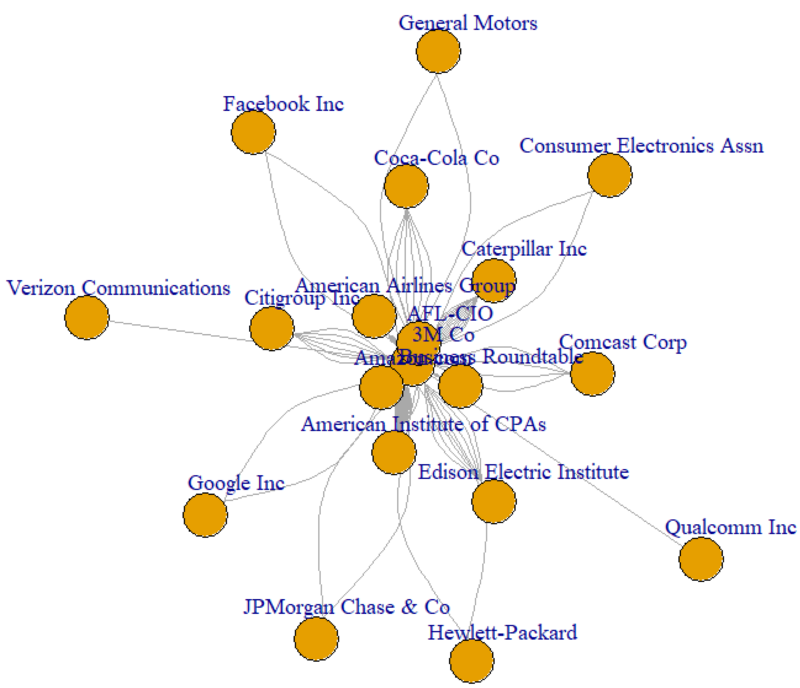
Meanwhile, Figure 5-4 presents a two-mode or bipartite network, where each square represents lobbying clients while the circles are actual bills, with the vertices (lines) between them representing the number of bills that each lobbying client lobbied for. In this case we are looking at lobbying clients who lobbied over 50 times (i.e., submitted multiple lobbying reports indicating a specific lobbying bill). In some cases, these were bills initially proposed before the House of Representatives, while in other cases it was bills presented in the Senate. Thus, in the case of figure 5-4, one vertex represents the link between a lobbying client and a given Senate or House bill that the client lobbied for at least 50 times.

Figure 5-2: Word Cloud

Source: https://www.opensecrets.org/bulk-data

Some clients, like Microsoft and Facebook, for example, also referenced non-material concerns as part of their immigration lobbying efforts, like the Deferred Action for Childhood Arrivals (DACA). Referencing DACA could be regarded as an outcome that is less economic driven and more social or humanitarian, since most part of DACA seeks to establish a path to documented status for individuals who were brought to the United States as children and fulfilled a number of conditions.[26]

Figure 5-3: Immigration Lobbying Network



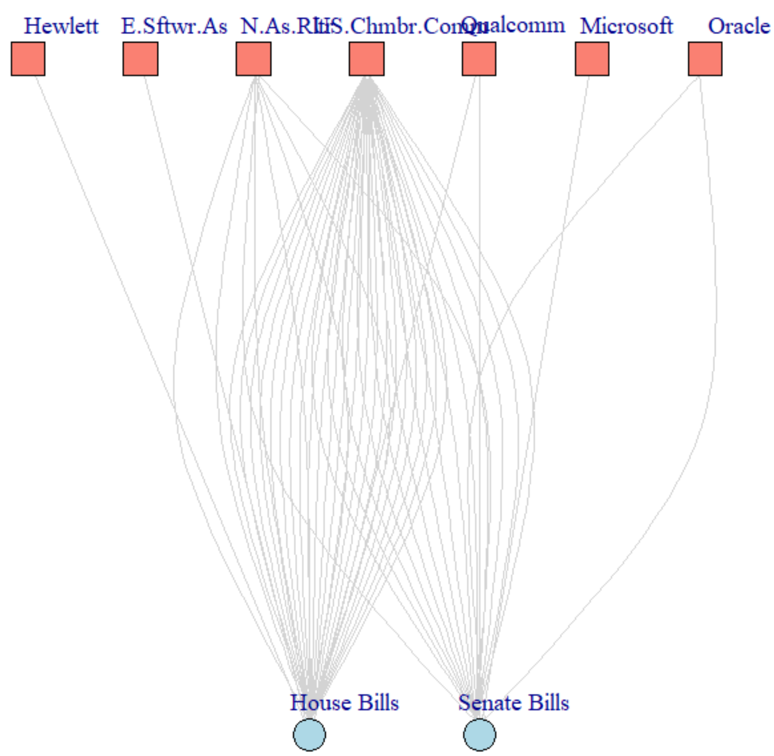
Source: https://www.opensecrets.org/bulk-data

However, it is also worth noting that individuals eligible for DACA are given something that resembles more a work-permit than an actual path to citizenship. Moreover, in many of the reports in which clients like Microsoft and Facebook cite DACA as a specific-immigration related issue, said reports also tended to list other policy outcomes, like ensuring that more worker visas could be procured for foreign workers (especially visas that could ensure the

[26] Specifically, on June 15, 2012 Janet Napolitano, then Secretary of Homeland Security, announced that individuals who were under the age of 31 (as of June 15, 2012), came to the United States prior to turning 16 years of age, had continuously resided in the United States since Jun 15, 2007, were physically present in the US on June 15, 2012, had no lawful status in the US, had either graduated or were in the midst of competing a degree (could be high school, general education (GED) certificate, or had been honorably discharged from the Coast Guard or Armed Forces of the United states), and had never been convicted of any felony, were eligible to apply for a two-year (renewable) lawful status in the United States. A status, though, that was not conducive to permanent residence nor citizenship.

entry of high-tech workers). Thus, even if firms like Microsoft and Facebook were motivated by humanitarian considerations in their sponsorship of DACA, overall, much of their respective immigration lobbying seems to be driven primarily by economic considerations. Particularly, considerations that regard the entry of foreign-born workers to help meet production objectives.

Figure 5-4: Bipartite Network



Source: https://www.opensecrets.org/bulk-data

If we refer again to Appendix Table A-1 we note that ten of the top 19 immigration lobbying clients, are firms (Microsoft, Oracle Inc., Intel, Cognizant Technology Solutions, Perspecta, Qualcomm Inc., Wing Formerly X Google Inc.[27], Accenture Lip, Texas

[27] X, or X Development LLC (formerly known as Google X) refers to quasi-secret google research and development facility founded by Google in 2010 (Secret Google lab "rewards failure" 2014). Project Wing refers to one specific project developed by X.

Instrument, and Facebook) while nine are trade associations (AmericanHort, U.S. Travel Association, Techserve Alliance, National Association of Home Builders, Business Roundtable, Entertainment Software Association, Consumer Electronics Association, National Restaurant Association, and the U.S. Chamber of Commerce). Based on their respective lobbying reports, firms were more inclined to support policies that facilitated the entry of high-skilled workers, whereas support for low-skilled immigration is more prominent among select trade associations (most notably the National Association of Home Builders, AmericanHort, and the National Restaurant Association). Even if there are anti-immigration actors like NumbersUSA among the top immigration lobbying actors, we can see how a) the majority of clients listing immigration as lobbying issue sought political outcomes that favored immigration entry, and b) were primarily driven or motivated by economic concerns.

5.2 Immigration Trends

Over the last forty years, immigration to the United States has featured individuals that could be characterized either as being non-routine, low-skilled workers, or non-routine high-skilled workers (Basso, Peri, and Rahman 2020). While immigrants work in all types of occupations across economic sectors, they tend to concentrate more in certain occupations than in others. Often, questions of language and even documentation status, incentivize low-skilled immigrants to gravitate more towards occupations in which the need for communication skills is minimal (Basso, Peri, and Rahman 2020; Peri and Sparber 2009; Ottaviano and Peri 2012). On the other hand, given that language is not as much an issue for many low-skilled native-born workers, it is more likely that many end up working in communication-intensive occupations. In this sense we see that the threat of substitution of low-skilled native workers by low-skilled immigrant workers is minimal (Basso, Peri, and Rahman 2020; Peri and Sparber 2009; Ottaviano and Peri 2012).

In the case of non-routine high-skilled immigrants, language-skills do not play a role in terms of the types of occupations in which the latter are more likely to concentrate. However, high-skilled immigrants are also more likely to concentrate in certain occupations than others although for different reasons than their low-skilled counterparts.

For starters, many high-skilled immigrants often enter the United States via association with universities, high-tech firms, or research centers (Kerr et al. 2016). In addition, high-skill immigrants more often settle in urban settings, that are more likely to house employment sites and other amenities for STEM or business occupations, for example, than in rural settings (Kerr et al. 2016). Examples of this can be seen with the rise of certain regional clusters, which often attract high-skilled professionals such as financial hubs like New York City and Chicago, as well as Hollywood for the entertainment industry, or Silicon Valley in the case of the tech sector (Diamond 2016; Kerr et al. 2016). For both low and high-skilled immigrant workers, there is also a feedback effect, whereby someone may through a friend, relative, or contact, find employment within a given city and even within the same sector or even company. (Kerr et al. 2016).

As with low-skilled immigration, evidence suggests that the substitution effect of high-skilled immigrants on their native-born counterparts is not significant, and quite the opposite, high-skilled immigrants are often regarded as innovators or job creators (Lin 2019; Ma 2020). That the United States is the largest immigration recipient country is no accident either. On the landscape of high-skilled immigration, there is an ongoing global race for talented professionals among developed economies (High-skilled immigration and the growing concentration of US innovation n.d.). Both low and high-skilled immigrants introduce an overall net benefit for the communities in which they settle, through their work and also through their consumption of ancillary goods and services (the latter are usually provided by natives) (Low-Skilled Immigration Brings Economic Benefits for U.S. Consumers, Employers and Skilled Workers; Also Imposes Some Costs 2011).

While this is not to suggest that there is never any overlap between migrants and natives in terms of the jobs they perform, on average, native-born worker and immigrant worker are *imperfect substitutes* of one another in terms of the work they carry out (Card and Peri 2015; Peri and Sparber 2009). This *imperfect substitutability* can be in part attributed to the fact that comparatively speaking low-skilled immigrants tend to have limited language ability (when speaking and/or writing in English) when compared with their native counterparts (Card and Peri 2016; Lewis 2013). This discrepancy in language ability, along with the undocumented status of some immigrant workers, has often contributed to the specialization of low-skilled immigrants in occupations intensive in manual and physical labor, and where English communication skill requirements are basic. While low-skilled native-born workers tend to specialize in jobs that are more intensive in communication-language tasks (Card and Peri 2015; Peri and Sparber 2009).

In fact, this *imperfect substitutability* has helped attenuate some of the more adverse effects of automation on native-born labor (Cadena and Kovak 2016; Peri and Sparber 2009). Since the majority of immigrants to the US have worked in predominantly non-routine low-skill service (low-wage) occupations, this may have contributed economically (through taxes for example) to facilitate the upgrade (via education) of displaced native-born routine workers (Basso, Peri, and Rahman 2020; Cadena and Kovak 2016).

5.3 Assessing the Impact of Automation on Labor.

Part of the problem inherent to measuring and estimating the effects of automation, or new technologies more broadly, on labor has to do with limitations of existing data. Although different sources of data provide useful information about the U.S. workforce (in terms of trends, composition of occupations, employability of tasks, as well as the number of computers, robots, or other types of machinery at the industrial level) it is very difficult to establish and assert a causal relationship between the rise and proliferation of new technologies (from AI to robots) and employment trends (United States Government Accountability Office (GAO): Report to Congressional Office Requesters 2019).

In the 2019 report *Workforce Automation: Better Data Needed to Assess and Plan for Effects of Advanced Technologies on Jobs*, the United States Government Accountability Office (GAO)[28] asserted that, up until the publication of the report, no comprehensive data tracking firms' adoption and use of advanced technologies existed, making it difficult to establish whether any changes to the composition of the U.S. workforce were due to changes in technology, or other factors (United States Government Accountability Office (GAO): Report to Congressional Office Requesters 2019). To some extent, there is some dissonance among existing sources of data since data on employment and employment trends is provided at the industry level, while data on the effects of technology is provided at the task or occupational level. (United States Government Accountability Office (GAO): Report to Congressional Office Requesters 2019).

Moreover, there has been inconsistency in the way in which emerging technologies have been tracked (United States Government Accountability Office (GAO): Report to

[28] The GAO is a legislative branch agency that provides auditing, evaluation, and investigative services for the US Congress (U. S. Government Accountability Office n.d.).

Congressional Office Requesters 2019). For example, the US census used to have questions about the use of self-service in gas stations, until the technology became so ubiquitous that it was dropped from the census. With the recent rise of self-service technology in sectors like restaurants, the census has once again added questions about self-service into its surveys, providing some more data-points on the question of self-service, albeit one that has gaps between certain periods (United States Government Accountability Office (GAO): Report to Congressional Office Requesters 2019).

Table 5-1: Work Activities[29] — Importance of Interacting with Computers: [30] Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information)

	2004-2009	**2011-2015**	**2016-2020**
% Of workers surveyed who indicated that *working with computers* is not very Important	**42.55%**	**7.94%**	**5.87%**
% Of workers surveyed who indicated that *working with computers* is very important	**57.45%**	**92.06%**	**94.13%**

Source: https://www.onetonline.org/find/descriptor/result/4.A.3.b.1

Lastly, given the limitations of the data, it becomes increasingly hard to be certain that there is a causal relationship between automation and labor. Thus, it is very difficult to assess whether trends in employment can be attributed to the introduction of new machinery

[29] See p. 11 https://www.onetcenter.org/dl_files/MS_Word/Generalized_Work_Activities.pdf, for more information on wording of question.
[30] How Important is, "using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information" for your occupation (scale from 1-5, with 1 being not very important and 5 being very important. In the first row we find the percentage of surveyed individuals who responded 2 or less, while in the second row we find individuals whose response 3,4, or 5).

(i.e., due to automation) or some other factors or potential confounders (United States Government Accountability Office (GAO): Report to Congressional Office Requesters 2019). Moreover, the more uncertainty there is involving the causal mechanism of automation and labor the less certainty there is regarding predictions of which occupations are more susceptible to automation's risks versus which occupations stand to benefit more from it.

Table 5-2: Work Activities [31]— Level of Interacting with Computers: Using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information)

	2004-2009	**2011-2015**	**2016-2020**
% Of workers surveyed who indicated that the level of working *with computers* being necessary to perform their current work was very low or unnecessary	**29.89%**	**3.81%**	**2.94%**
% Of workers surveyed who indicated that the level of working *with computers* being necessary to perform their current work was necessary	**70.21%**	**96.19%**	**97.06%**

Source: https://www.onetonline.org/find/descriptor/result/4.A.3.b.1

However, we can gauge for general trends regarding the use of technology by labor. Tables 5-1 and 5-2 summarize, for example, how important working with computers has become across occupations. Table 5-1 reveals that computers are now prevalent virtually

[31] Level of rating indicating the degree to which the following descriptor is needed or required for to perform the occupation "using computers and computer systems (including hardware and software) to program, write software, set up functions, enter data, or process information" for your occupation (scale from 0-7, with 0 being low or none at all, while 7 being very high. In the first row we find the percentage of surveyed individuals who responded 1 or less, while in the second row we find individuals whose response 2-7).

across the workforce as the percentage of respondents who commented that using computers was not very important to their work, has substantially decreased from 42.55% (between 2004-2009) to about 5.87% during the period 2016-2020.. By contrast, we see more workers have responded that the use of computers is important for their work as seen in the second row of Table 5-1. Likewise, in Table 5-2 we also note an increase in the percentage of workers who indicate that working with computers is necessary for their current work. In fact, from 2016 to2020 about 97.06% of those workers surveyed stated that knowing how to work with computers was necessary for their line of work.

Moreover, as we have seen, it is possible to differentiate routine from non-routine tasks. Building on this distinction it is possible to assess the effects of automation at the occupation level. As occupations represent a collection of tasks performed by labor in terms of similar objectives, methodologies, materials, products, worker actions, or worker characteristics, we can conclude then that some occupations are inherently *routine* while other occupations are inherently *non-routine* (Autor, Levy, and Murnane 2003; Office and Administration 1991). Furthermore, automation has reduced demand for workers in occupations that are intensive in routine task (Reijnders and de Vries 2018). By contrast, automation and new technologies have helped to increase demand for non-routine occupations (Reijnders and de Vries 2018).

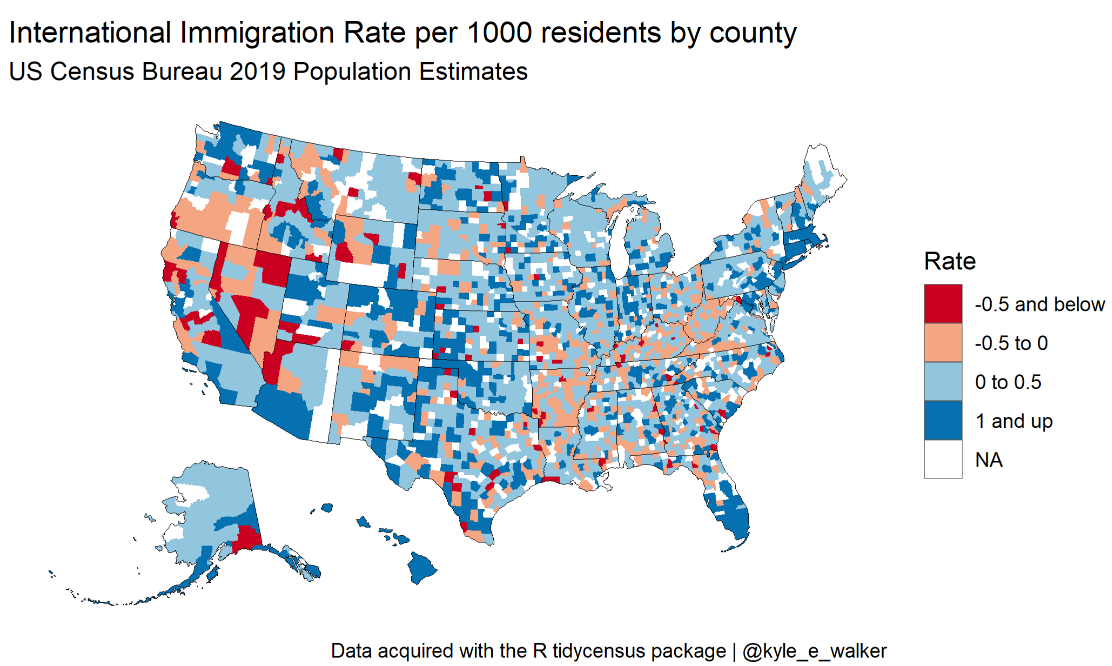
Differentiating routine from non-routine occupations permits us to identify two things. First, we can account for changes over time in the occupational distribution of employment (Autor, Levy, and Murnane 2003, 1292). In other words, with the passing of time there may be an increase in the number of non-routine occupations with a corresponding decrease in the number of routine occupations. Moreover, we can also assess whether the changes in the distribution of occupations is derived by changes in technology (i.e., whether there has been a *complementary* or *additive* effect to automation or a *displacement* effect of automation on occupations) (Autor, Levy, and Murnane 2003).

As much of the industrial production has either been outsourced to trade, or simply, automated, there has also been a rise in service-based employment across the United Sates (Autor and Dorn 2013). On the one hand, the transition to a service-based economy has enabled a rise in demand for high-skilled non-routine labor (possessing at least a university degree or higher) to complement the new labor exigencies enabled by the advent of new technologies (e.g., financial analysts, software-engineers, and medical professionals, among others (Autor and Dorn 2013; Basso, Peri, and Rahman 2020)). Parallel to the rise in demand for non-routine, high-skilled service professionals, there has been a corresponding increase in the demand for non-routine low-skilled labor to perform non-routine manual intensive services work (for example, food preparation, housekeeping, landscaping, and construction) (Basso, Peri, and Rahman 2020). In part, demand for non-routine low-skilled service labor may have also been fueled by non-routine high-skilled professionals' demand for more service amenities (e.g., dining, daycare, and construction) (Diamond 2016).

Looking at the supply of immigration to the United States since the 1970s reveals that the skill composition of migrants has mirrored the changing employment landscape. Since the 1970s immigrants have been predominantly non-routine high-skilled or non-routine low skilled (Basso, Peri, and Rahman 2020; Peri 2016). In fact, the average migrant worker to the US has been qualitatively different from the average native-born worker in terms of their skills and the sectors in which they work. Concordantly, immigrants have usually worked in different occupations and industries than their native-born counterparts (Basso, Peri, and Rahman 2020; Cadena and Kovak 2016; Peri and Sparber 2009).

Usually, non-routine low-skilled migrants tend to concentrate in manual-service industries, while non-routine high-skilled immigrant workers would likely work in predominantly analytical types of industries (Baso, Peri, and Rahmn 2020; Cadena and Kovak 2016; Peri and Sparber 2009). In addition, in the last four decades, immigrants have tended to concentrate geographically in distinct regions than their native-born workers and have also exhibited greater willingness to relocate across the United States in the face of exogenous economic shocks (Cadena and Kovak 2016; Molloy, Smith, and Wozniak 2011; Peri and Sparber 2009). As we can see in figure 5-5, there has been a rise in the number of immigrants in primarily urban centers, as well as in several rural counties.

Figure 5-5: Net International migration per 1000 residents between 2018 and 2019.



Given that the average migrant to the US can be characterized as possessing non-routine skills, we can expect that firms and trade associations from more service-oriented and analytically based industries will lobby for immigration. However, as we have also seen, the complexity and costliness of lobbying in the current political landscape means that it will be very unlikely to find firms treating immigration-lobbying as a proverbial faucet, which they simply turn "on" or "off" depending on whether their demand for immigrant labor increases or decreases. Instead, a better approach would be to account for instances in which firms or trade associations, already invested in the lobbying process, *adjust* their lobbying behavior towards immigration-specific issues (Kerr, Lincoln, and Mishra 2014, 372).

We can then ask whether the qualified effects of automation on labor (*displacement, complementary,* and *additive* effect) help explain instances in which firms have *adjusted* their lobbying behavior. For example, the administration of Donald Trump, in several instances, sought to curtail the entry of both documented and undocumented migrants to the United States (A 501tax-exempt, NW, and Washington n.d.). Such initiatives were met with both support and condemnation (somewhat mirroring the degree of ongoing political polarization). For the purpose of this dissertation we can ask a) which firms and trade associations lobbied against such initiatives (or even favorably), and b) whether the effects of automation on labor influenced firms' decisions and direction of lobbying (positive, null, or negative) in response to said policies. To answer these questions we formulate two hypothesis.

Hypothesis 1: We can expect that increased reliance on technology is conducive to an increase in immigration lobbying among firms that rely heavily on non-routine immigrant workers.

Given that the *displacement effect* of automation is more likely to occur among occupations that are *routine task* intensive, we can expect an overall contraction in firm or trade association lobbying for immigration to produce goods and services in routine industries.

Hypothesis 2: We can expect that increased reliance on technology is conducive to a contraction in immigration lobbying among firms that rely on routine workers.

In short, the theory I propose is that given the qualified effects of automation on labor (displacement, complementary, and additive) the expectation is that automation will increase demand for non-routine labor, while contract demand for routine labor. Moreover, given that immigrants tend to specialize and concentrate in specific industries, I propose that as automation increases demand for non-routine work in these industries, we can expect a corresponding increase in immigration-lobbying from these firms and trade associations.

It should be noted that the task-based models articulated by scholars like Daron Acemoglu and David Autor regard the categories of *routine/non-routine* as being mutable, rather than static. In other words, today's non-routine occupations may become tomorrow's routine occupations. This idea of fluidity can help us explain how and why we see different periods of booms and busts for occupations across different epochs. Thus, the best way to assess the impact of automation and technology on labor and by extension firm-immigration lobbying would have to be longitudinal keeping track of the elements like the types of new technology that exist along with data on the types of skills necessary or inherent to any given occupation. Nevertheless, the theory outlined in this chapter proposes that the qualified effects of automation developed by task-based analysis can help predict instances in which new technologies can fuel or increase firm demand for non-routine immigrant workers, reflected via their lobbying.

CHAPTER 6. RESEARCH DESIGN AND DATA

In this chapter, I will expand on the research design and sources of data that I use for my analysis. In particular, I will explain how my analysis builds on and combine elements from the research designs of other authors.

6.1. Dependent Variable

Through political lobbying, domestic actors can assert their policy preferences—whether in favor or in opposition. Here we understand lobbying as spending political capital, wherein actors like firms show support for a policy maker's position on a given policy (Lake 2009). The closer the policy is to the firm's *ideal*, the more the firm will support said policymaker (Peters 2017, 20-21).

Consistent record keeping on lobbying activity in the United States was made possible with the passing of the Lobbying Disclosure Act (LDA) in 1995, and with the subsequent passing of the Honest Leadership and Open Government Act in 2007.[32] Since 1996, lobbyists are required to file a semi-annual report to the Secretary of the Senate's Office of Public Records (SOPR) (Guide to the Lobbying Disclosure Act n.d.). In these reports, lobbyists must specify the name of the client they are lobbying on behalf of, the amount of funds that the lobbyist has received from their individual client(s), and the pre-specified issue(s) for which they are lobbying for on behalf of their client(s) (e.g., trade, immigration, taxes) (Kerr, Lincoln, and Mishra 2014, 347).

Hence, the LDA has facilitated access to detailed information about lobbying activities, including issues lobbied, individual lobbyists, and lobbying costs (Facchini,

[32] In 2007 the LDA was modified by the Honest Leadership and Open Government Act ((Kerr, Lincoln, and Mishra, 347). This act now requires organizations to detail substantial information surrounding their lobbying activities (Kerr, Lincoln, and Mishra, 347).

Mayda, and Mishra, 2011). Because of the LDA, it is possible to associate empirically the lobbying expenditures of companies with the very specific policies that they target (Kerr, Lincoln, and Mishra 2014, 347). Data on lobbying expenditures are compiled from the Center for Responsive Politics (CRP), a nonpartisan, independent, and non-profit research group that tracks the effects of money and lobbying on elections and public policy in the United States (A 501tax-exempt, NW, and Washington n.d.).

6.2 Independent Variable

By observing the tasks inherent to a given occupation, it is possible to assess whether the work carried out by a worker in this occupation entails procedures that can be methodically ascertained and replicated by a machine or computer, i.e., whether the tasks associated to an occupation are routine or not (Autor, Levy, and Murnane 2003).[33] To identify the task composition of occupations, I will rely on the United States Department of Labor's Occupational Information Network (O*NET) database. O*NET is developed under the sponsorship of the U.S. Department of Labor's Employment and Training Administration

[33] As part of their analysis, Autor, Levy, and Murnane (2003) selected specific task-measures used by the DOT in their 1977 and 1991 editions. While the DOT relied on many more measures as part of their analysis of work, Autor, Levy, and Murnane (2003) proposed that selected task measures best approximated the different task categories they had proposed (i.e., routine cognitive, routine manual, non-routine cognitive, and non-routine manual tasks). The DOT tasks-measures selected by Autor, Levy, and Murnane (2003) were GED-MATH (General Educational Developments, Mathematics) and DCP (Direction Control Planning) to capture the extent to which a worker would have to perform non-routine cognitive tasks within a given occupation. In this sense the more an occupation requires workers be able to perform higher levels of GED-MATH and/or DCP, the more said occupation could be said to be non-routine cognitive (Autor, Levy, and Murnane 2003, 1293). The authors selected the variables STS (Set limits, Tolerances, or Standards) as an indicator for routine-cognitive occupations (i.e. the higher the level of STS was associated to perform work, the more said work was deemed routine cognitive). The variable FINGDEX (Finger Dexterity) was similarly used to measure the extent to which routine manual tasks were necessary cross-occupationally. Finally, to account for non-routine manual occupations the authors looked how important the EYEHAND (Eye-Hand-Foot Coordination) variable across occupations (Autor, Levy, and Murnane 2003, 1293). In essence, for any give occupation the higher the value associated with one of the variables the more said occupation could be justified as being non-routine or routine (Autor, Levy, and Murnane 1293-1294).

through a grant to the North Carolina Department of Commerce (About O*Net n.d.)[34]. In looking at the O*NET database it becomes possible to obtain information regarding the task-content of occupations. Furthermore, the O*NET database often updates information regarding the requirements, skills, and tasks inherent to occupations (Mariani 1993).

Given that every occupation requires a different mix of knowledge, skills, and abilities while performing a variety of tasks and activities, O*NET utilizes a Content Model to capture the different requirements (including mix of knowledge, skills, and abilities) and the variety of activities and tasks necessary to perform work within a given occupation (O*NET OnLine Help: O*NET Overview, n.d.). The distinguishing characteristics of an occupation are converted into standardized and measurable set of variables called *descriptors* (O*NET OnLine Help: O*NET Overview, n.d.). In total, there are 277 O*NET descriptors used to describe and measure the content of different occupations (O*NET OnLine Help: The Database, n.d.).

All O*NET descriptor analyses of occupations are made with respect to the taxonomy established by the Standard Occupational Classification (SOC) System (O*NET OnLine Help: O*NET Overview, n.d.). The SOC is a U.S. federal statistical standard used by federal agencies to classify workers into occupational categories for the purpose of collecting, calculating, and/or disseminating data (U.S. Bureau of Labor Statistics 2018). Every SOC occupation is issued a six-digit code and corresponding occupation title. For example, the SOC code 47-2031 corresponds to the occupation title Carpenter; the SOC code 25-106 corresponds to Political Science Teachers, Postsecondary; and the SOC code 21-1212

[34] This page includes information from O*NET Resource Center by the U.S. Department of Labor, Employment and Training Administration (USDOL/ETA). Used under the CC BY 4.0 license. O*NET® is a trademark of USDOL/ETA.

corresponds to the occupation of cardiologist (U.S. Bureau of Labor Statistics 2018). Since 2019, the O*NET-SOC occupation taxonomy consists of 1,016 distinct occupational titles (Gregory et al. 2019).

It is worth noting that the O*NET database is based on survey data, which is randomly distributed to selected businesses, from which there is an additional random selection of incumbent workers who are asked to complete these surveys (O*NET® Data Collection Overview." N.d.). These surveys are conducted on a yearly basis (U.S. Department of Labor Employment and Training Administration 2012). Each survey generally consist of a series of Likert Scales[35], which ask descriptive type questions to an incumbent worker like, "How important is ARM-HAND STEADINESS[36] to the performance of your current job."[37] In the survey, the worker has to mark one of the following options on a scale, "Not Important (1), Somewhat Important (2), Important (3), Very Important (4), Extremely Important (5)"[38]. Responses to these surveys are then collected and analyzed by the Department of Labor and the Employment and Training Administration (U.S. Department of Labor Employment and Training Administration 2018, 74). For each occupation, a mean

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[35] A Likert Scale (named after psychologist Rensis Likert who first introduced it (Likert 1932)) is scale featured across surveys, often seeking to capture a level of agreement/disagreement with a given statement or question (Carifio and Perla 2007).

[36] "The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position." For more information, please see: https://www.onetcenter.org/dl_files/MS_Word/Abilities.pdf.

[37] For all occupations O*NET relies on like the importance, level, and extent to which any given descriptor is necessary for the performance of work within any given occupation (O*NET OnLine Help: Scales, Ratings, and Standardized Scores N.d).

[38] "The O*NET Data Collection Program provides several hundred ratings, based on responses by the sampled workers to the O*NET questionnaires. It is not feasible to ask each respondent to provide information for all data elements. To reduce the burden on respondents, the questions have been organized into three questionnaires, each containing a different set of questions. The sampled job incumbents for each occupation are randomly assigned one of the three questionnaires. All respondents are also asked to complete a task questionnaire and provide some general demographic information. Abilities and Skills information is developed by occupational analysts using the updated information from incumbent workers" For more information, please see: (O*NET® Data Collection Overview N.d).

(average) is calculated for each descriptor.[39] For example, workers working in occupation x, may have responded on average that ARM-HAND STEADINESS had a level of importance of “3 (important)” along Likert-scale between 1 and 5.

These Liker-scale descriptors, with values from 1 to 5, are then transformed into a standardized scale from 0 to 100 through the following equation: $S = \left(\frac{O-L}{H-L}\right) * 100$, where **S** is the standardized score, **O** is the original rating score on the scale, **L** is the lowest possible score on the rating used, and **H** is the highest possible score on the rating (O*NET OnLine Help: Scales, Ratings, and Standardized Scores N.d). If the average response to the question about the importance of the *ability* ARM-HAND STEADINESS for occupation *x* was “important (3)” (on the importance scale of 1 to 5), then this would be translated to: ((3-1)/(5-1))* 100 = (2/4)*100 = 50 in the O*NET importance scale. Thus, for occupation *x* the ability ARM-HAND STEADINESS has level of 50 (out of 100) in the importance (now standardized) scale.[40] In my dissertation, unless stated otherwise, any reference to O*NET measures will be made with respect to these standardized average descriptor scales.

Using these scales, it is possible to conduct a cross-occupational comparison along any given indicator. For example, for the occupation astronomer (SOC code: 19-2011.00), on a standardized scale ranging from 0 to 100, *mathematical knowledge* emerges with a level of importance of 100; i.e., it is extremely important to have sophisticated knowledge of mathematics and mathematical reasoning in order to perform work as an astronomer. By contrast, for the occupation of model (SOC code: 41-9012.00), on the same scale (0 to 100)

[39] See ((U.S. Department of Labor Employment and Training Administration 2018, A.16 for more information).
[40] See (O*NET OnLine Help: Scales, Ratings, and Standardized Scores N.d) for more information.

the level of importance of mathematical knowledge is measured at 10, meaning that mathematical knowledge is not very important to perform work as a model.

It is worth noting that the level of detail and information the O*NET database provides, can itself be a drawback as it may be hard to determine which *descriptor* to use to capture the difference between routine and non-routine tasks cross-occupationally (Acemoglu and Autor 2011, 1078). Given this challenge, I will rely on the O*NET task measures used by Acemoglu and Autor (2011) who suggest that their O*NET based measures most closely accord (or resemble) the DOT task measures used by Autor, Levy, and Murnane (2003) (Acemoglu and Autor 2011, 1079f38). These task measures essentially consist of Routine Cognitive, Routine Manual, Non-Routine Cognitive Analytical, Non-Routine Cognitive Interpersonal, Non-Routine Manual Physical, and Non-routine Manual Interpersonal. Additional information on these tasks measures can be found on appendix table A-5 of this dissertation. Observing the task composition of occupations permits us to see whether changes in the distribution of occupations across time and within industries, feature an increase in the number of non-routine occupations, with a simultaneous contraction in routine occupations.

6.2.1 Worker Information

In spite of the wealth of information the O*NET database provides regarding the nature of work inherent to any given occupation, O*NET does not provide any information pertaining to the individual features or characteristics of workers. For example, O*NET provides data on the average level of education and the average salary a worker earns within a given occupation, but not information on the percentage of foreign-born workers working in said occupation, information that is necessary for my analysis.

Although it would be ideal to have information on the number of immigrant workers firms employ, it is hard to obtain exact numbers of the status of firms' workforce. While it is possible to obtain data on the number of foreign-born workers by industry, this measure is not so easy to obtain at the firm-level; and relying on industry-level data, may be too broad a measure for any substantial analysis. Therefore, as a way to operationalize immigrant workforce by firms, I will rely on the Department of Labor's (DOL) Office of Foreign Labor Certification (OFLC) Annual Performance Data (Program and FLAG Resources | U.S. Department of Labor n.d.; Performance Data | U.S. Department of Labor n.d.).

The benefit of the DOL's OFLC Performance data is that it provides comprehensive data on the number of requested H-type visas and PERM in a given year—including which requests were certified as opposed to which requests were denied. It also provides information of who were the employers requesting these visas (for example, how many requests for H-1B visas were made by Microsoft and Amazon) and the name and description (including the SOC-Code) of the occupation of the employees (Performance Data | U.S. Department of Labor n.d.). Because the DOL's OFLC Performance data contained information on the SOC-Code of those workers who had been issued an H-type visa or PERM in a given year, it is possible to combine this information with, information from O*NET 26.0 data, which also utilizes the SOC classification system to evaluate occupations. For example, the occupation Management Analyst (SOC-Code 13-1111) was the occupation that obtained the greatest number of certified H-1B visas between 2015 and 2019 (a total of 59,9897 certified visas for this 4-year period).

As data from the DOL and O*NET reference SOC codes in their respective databases; I will merge average task-measurement of a given occupation, with individual worker data (like country of birth or citizenship status, for example) using the SOC codes. Merging occupation-specific task values from O*NET, with individual worker information from the DOL, should permit me to capture how changes in the task-composition of occupations and shifts in the distribution of occupations correspond with changes in the types of workers who work in these occupations.

6.2.2 North American Industry Classification System

All discussion regarding changes in the type of work within occupations, changes in the distribution of occupations, and changes in the type of labor composition of occupations (e.g., whether there are more immigrant workers working in occupation *x* across time) will be made with respect to US industries following the North American Industry Classification System (NAICS). Developed under the direction of the Office of Management and Budget (OMB), NAICS is currently one of the main industry classification systems. Along with the Standard Industrial Classification (SIC) System[41] it is used in the United States for the classification of business establishments into industries based on the similarity of their production processes (Executive Office of the President Office of Management and Budget 2017, p. 14). In addition to the United States, the NAICS industry classification system is used by Mexican and Canadian government agencies and businesses.[42]

[41] NAICS was developed with the intention of replacing the SIC (Executive Office of the President Office of Management and Budget 2017, 13). While presently most government agencies and business in the United States rely on NAICS, the SIC is system is still utilized by some agencies (e.g., the Securities Exchange Commission). For more information please see: https://www.sec.gov/files/aqfsn_1.pdf.

[42] NAICS was developed and adopted in 1997 under the cooperation of the U.S. Economic Classification Policy Committee (ECPC), Mexico's National institute of Statistics and Geography (INEGI) and Statistics Canada (Executive Office of the President Office of Management and Budget 2017).

The NAICS classification system groups establishments[43] based on the similarity of their production process. As with the Standard Occupation Classification (SOC) System, NAICS employs a numbering system to categorize industries. The NAICS numbering system relies on a five, sometimes six, digit code as part of its taxonomic and organizing scheme and a corresponding industry title (Executive Office of the President Office of Management and Budget 2017, 18). This numbering system follows a hierarchical structure, where the first two digits of any NAICS code correspond to an economic sector (the largest level of aggregation in the NAICS system), while the last digit (in some cases the last two digits) of the code corresponds to an industry (the lowest level of aggregation) (Executive Office of the President Office of Management and Budget 2017, 18).[44] For example, the industry code 111110 corresponds to the industry title *Soybean Farming*, the code 611310 corresponds to the industry title *Colleges, Universities, and Professional Schools*, while the code 722410 corresponds to the industry title *Drinking Places (Alcoholic Beverages: e.g. bars)* (Executive Office of the President Office of Management and Budget 2017). In its 2017 publication, NAICS classifies all economic activity into twenty sectors and lists a total of 1,057 industries ((Executive Office of the President Office of Management and Budget 2017, 14). Thus, in general, in this dissertation I reference industries or economic sectors with respect to NAICS categories, unless otherwise stated.

[43] As a statistical unit, NAICS defines an establishment as the smallest operating entity for which records provide information on the cost of resources—material, labor, and capital—employed to produce units of output (Executive Office of the President Office of Management and Budget 2017, 19).
[44] The six-digit NAICS coding system identifies particular industries and their placement within this hierarchical structure of the classification system. The first two digits of the code designate the sector, the third digit designates the subsector, the fourth digit designates the industry group, the fifth digit designates the NAICS industry, and the sixth digit designates the national industry ((Executive Office of the President Office of Management and Budget 2017, 18).

6.2.3 Technology and Labor

Differentiating routine from non-routine occupations is a necessary step in order to analyze the effects of automation on demand for labor. In line with Autor, Levy, and Murnane's (2003), automation should be positively correlated with changes in the cross-industry distribution of non-routine occupations, while inversely correlated to the distribution of routine occupations. The first question is whether automation can be documented and measured empirically in order to show: a) how closely (if at all) it is correlated with changes in the distribution of occupations by industry and by extension, b) how automation affects firms/trade associations' demand for immigrant (or immigration lobbying).

In their original work, Autor, Levy, and Murnane (2003, 1303) looked at how computer adoption—as well as investment in computer capital—impacted the distribution of routine and non-routine occupations at the industry level. A core assumption of Autor, Levy, and Murnane's (2003) analysis was that the advances in computer technology and the price of computers were exogenous to questions of the task-content of occupations as well as distributions of occupations (1287). Implicit to this assumption is the premise that technical advances are also exogenous to the question of tasks performed by labor, making computers both more efficient in their functions and comparatively cheaper to purchase as time passes (Autor, Levy, and Murnane 2003, 1287).

The authors use the declining price of computers and computer capital as the "causal force" of their model. This means that they measured the declining price of computers and computer capital to explain how, the cheaper computers become the more prevalent they are across industries, and thus the more they are used within industries for the performance of certain tasks (Autor, Levy, and Murnane 2003, 1287). The more computers are used across industries, the more likely it becomes that computers will displace labor from routine occupations, and by contrast, the more likely they (computers) will complement or increase demand for non-routine occupations by industry (Autor, Levy, and Murnane 2003). Similar to Autor, Levy, and Murnane (2003), I will build on their premise involving the exogeneity of technological advances, and declining prices in production technology—like personal computers, robots, and artificial intelligence (AI)—with respect to the task-composition of occupations.

One limitation, however, is the absence of consistent and reliable records regarding the adoption of different technologies by firms. While it is possible to gauge information of different technological adoptions at more aggregate levels (e.g., economic sector) as we will see in the next chapter, these measures are too broad and are susceptible to statistical inaccuracy and bias. Thus, in chapters 7 and 8, I will engage on the limited sources of data that exist, their shortcomings, and what types of analysis can be derived from using these measures. In sum, in this chapter I presented the main sources of data that I will use for my large-N quantitative and statistical analysis.

CHAPTER 7. DESCRIPTIVE STATISTICS

This chapter presents a survey of important descriptive statistics regarding technology use and immigration lobbying. Despite the growing interest among scholars and policymakers on the social and economic impact that technology has on labor, data that tracks individual firms' (e.g., Microsoft) reliance on labor and technology to meet their production needs is scarce and limited in terms of scope. Without this type of firm-level data, it is difficult to evaluate whether the technology adoption of individual firms can help explain those firms' lobbying patterns. As will be discussed in this chapter, existing data permits analysis to occur at the aggregate level of the economic sector, but not at the firm level.

7.1 Establishing the Routine Task Index

In line with Acemoglu and Autor (2011), and Goos, Manning, and Salomons (2014), and Guarascio et al. (2019), I have constructed a routine task index (RTI) which captures the extent to which a given SOC-occupation[45] is routine, expressed in equation 1 below. (More information on the distinct components of equation 1 can be found in appendix table A-5).

Equation 1: The Routine Task Index (RTI)

$$|RTI_k| = |RC_k + RM_k - (NRCA_k + NRCI_k + NRM_k + NRMIA_k)|$$

Equation 1 expresses the routine task index of a given SOC-occupation (denoted by the subscript k). Data and information on occupations used to create the RTI seen in equation 1 was taken from the O*NET 26.0 database (released in August 2021), which provides information on the characteristics for a total of 873 occupations. (For more information on

[45] SOC-occupations refers to the Standard Occupational Classification System used by the U.S. federal government to classify workers into occupational categories (for more information see chapter 4) (U.S. Bureau of Labor Statistics 2018).

how O*NET evaluates and catalogues the content of occupations see chapter 6.) (O*NET® Database Releases Archive at O*NET Resource Center n.d.).

Table 7-1: Types of Routine and Non-Routine Activity: Examples

	Routine	**Non-Routine**
Cognitive/Analytic	Record keeping Calculating	Managing people Persuading others
Manual/Physical	Stacking objects Sorting papers	Janitorial services Cultivating and picking crops

This RTI builds on the logic of Autor, Levy, and Murnane (2003) work, who posited that we can think of tasks and, by extension, occupations as primarily producing work that is cognitive or manual-based, in addition to being routine and non-routine (see Autor, Levy, and Murnane 2003, 1286). From this initial typology we see that manual/physical as well as cognitive occupations can be routine and non-routine (see table 7-1 for more information). Thus, the RTI in Equation 1 builds on this logic and can be understood as the absolute value of the sum of the standardized values of the *Routine Cognitive* (RC) indicator, *Routine Manual* (RM) indicator minus the sum of the *Non-Routine Cognitive Analytic* (NRCA) indicator, the *Non-Routine Cognitive Interpersonal* indicator (NRCI) the *Non-Routine Manual* (NRM) indicator, and the *Non-Routine Manual Interpersonal Adaptability* (NARMIA)[46] (Acemoglu and Autor 2011; Cirillio et al. 2019; Goos, Manning, and Salomons

[46] Please note that the RTI used by scholars like Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) did not consist of finding the absolute value of the difference between the routine indicators and the non-routine indicators. In these works, the lower the value of the RTI, the less routine an occupation is said to be. Thus, a low negative RTI would be suggestive that the occupation in question was non-routine. I decided to make the RTI based on the absolute value, in order to make interpreting the RTI score for a given occupation more intuitive. I.e., the larger the number is now, the less routine or more non-routine its respective occupation is.

2014; Guarascio et al. 2018) (for more information on the composition of each indicator see Table A-5 of the appendix).

The RC indicator captures the degree of repetitiveness, standardization of tasks, importance of being exact and accurate across occupations. The RM indicator proxies the degree of repetitiveness and of pre-determination of manual operations across SOC-occupations. In turn, the NRCA indicator reports the extent to which, thinking creatively, analyzing and reporting data, and interpreting information for others, are necessary tasks of a given occupation. Furthermore, the NRCI indicator captures the importance of tasks like establishing and maintaining social relationships, along with guiding and motivating subordinates, and coaching others. The NRM indicator, for its part, captures the degree of manual dexterity needed to perform tasks within a given occupation. Lastly, although not used by Acemoglu and Autor (2011), I also include the Non-Routine Manual Interpersonal Adaptability (NRMIA) indicator, which looks at how important it is for workers to be able to perform work that is manually and physically demanding while also requiring them to possess a high degree of "social intelligence" (Cirillo et al. 2019; Guarascio et el. 2018). For example, hospitality workers suchlike waiters and waitresses engage in physically demanding work but must also have good social and interpersonal skills.

Thus, equation 1 requires us to find the difference between the sum of the routine indicators (RC + RM) on the one hand, minus the sum of non-routine indicators (NRCA + NRCI + NRM + NRMIA), on the other hand. As discussed in chapter 6, I transformed the Likert-scale descriptors (see Table A-5 in the Appendix) with values of 1 to 5, into a standardized scale from 0 to 100 through the following equation: $S = \left(\frac{O-L}{H-L}\right) * 100$, where **S** is the standardized score, **O** is the original rating score on the scale, **L** is the lowest possible score on the rating used, and **H** is the highest possible score on the rating (O*NET OnLine Help: The Database n.d.).[47] [48] Thereafter, I calculated the average of the standardized descriptor and divided that by 100, which yields a number between 0 and 1, for each indicator.

To give an example, if we look at the Routine Cognitive (RC) indicator and its respective descriptors for the SOC-Occupation 27-2011 (Actors), we see that the standardized scores for the descriptors "Importance of Being Exact or Accurate", "Important of Repeating the Same Task" and "Structured versus Unstructured Work" are 83, 52, and 58, respectively. Thereafter, if we calculate the average of these three scores and divide that by 100, we get the Average Routine Cognitive (RC) indicator score for the occupation of actors as being 0.64. Thus, the RC indicator for all 873 occupations entails obtaining the average of the descriptors corresponding to a given indicator. If we continue looking at the SOC-occupation 27-2011 (Actors) we get the following measures: RC = 0.85, RM = 0.33, NRCA= 0.57; NRCI = 0.59, NRM=0.32; NRMIA = 0.75. Now, if we substitute these numbers into equation, we can create equation 2 below.

Equation 2: RTI for Actors

$$|RTI_{Actors}| = |RC_{Actors} + RM_{Actors} - (NRCA_{Actors} + NRCI_{Actors} + NRM_{Actors} + NRMIA_{Actors})|$$

$$= |(0.85 + 0.33) - (0.57 + 0.59 + 0.32 + 0.75)|$$

[47] E.g., If the average response to the question about the importance of the *ability* ARM-HAND STEADINESS for occupation *x* was "important (3)" (on the importance scale of 1 to 5), then this would be translated to: ((3-1)/(5-1))* 100 = (2/4)*100 = 50 in the O*NET importance scale. Thus, for occupation *x* the ability ARM-HAND STEADINESS has level of 50 (out of 100) in the importance (now standardized) scale.[47] In my dissertation, unless stated otherwise, any reference to O*NET measures will be made with respect to these standardized average descriptor scales.

[48] It should be noted that in the case of the O*NET indicators nested under the Work Context Category, I relied on the Context (CX) scales, which similarly to the Importance scales, analyzed occupations along Liker-scale descriptors with values of 1 to 5 for all occupations being analyzed (for more information please see: https://www.onetcenter.org/dl_files/DataDictionary14_0.pdf).

$= |1.18 - 2.23|$

$= | - 1.05 |$

$= 1.05$

As can be seen in Equation 2 above, the absolute value of the RTI for SOC-Occupation 27-2011 (Actors) comes out to 1.05.

When looking at the RTI across all 873 occupations we see SOC-Occupation 29-1129 (Art Therapist) has the highest (1.92) absolute value per the RTI, making this occupation the "least routine occupation." At the other end, we find the SOC-Occupation 51-6021 (Pressers of Textile, Garment, and Related Materials), with and absolute value RTI score of 0.35, making this the most "routine occupation." Table A-3 in the appendix summarizes the five least, middle, and most routine occupations according to the RTI. Thus, the lower the absolute value of the RTI score of a given occupation is, the more routine this occupation is and therefore, the more likely automation will displace someone r working within this occupation.

7.2 Foreign-Born Worker Permits

Presently there are about 185 different types of visas issued by the U.S. government allowing entry and various periods of residence to foreign-born individuals. We can separate these visas into two types of categories: the Nonimmigrant visas that allow for the temporary entry and stay of foreigners into the United State, and Immigrant visas, intended to allow entry and permanent settlement to foreigners in the United States (Directory of Visa Categories (state.gov)). Table A-4 in the appendix, provides a summary and description of the different types of temporary worker permits (visas) issued by the United States government.

Among Nonimmigrant visas, we find a variety of distinct types and categories of visas serving different functions. There are temporary visas issued to diplomatic personnel working for a foreign embassy or consulate as well as working for international organizations (e.g., the UN, the World Bank and others). There are also Nonimmigrant visas and permits allowing the temporary entry and stay as tourists or part of an exchange program. In addition, there are visas that allow individuals to entry the US for the purposes of study. Furthermore, we find temporary Nonimmigrant visas that permit entry to foreigners to work inside the United States. Finally, we also find a category of Nonimmigrant visas issued to the direct family members (e.g., children or spouses) of individuals issued a temporary work permit (Directory of Visa Categories n.d.).

7.2.1 H-Type Visas

Visas like the H-1B[49] [50], H-2A[51], and H-2B[52] as well as the Program Electronic Review Management (PERM), a Labor Certification[53] process, are quite useful when it

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[49] The H-1B Visa refers to a conditional authorization of foreigners granted by the United States Federal government that allows American employers to employ foreign workers in specific specialty occupations. A specialty occupation requires that the applicant possess specialized knowledge, at least Bachelor's Degree, or the equivalent in terms of work experience (H-1B Specialty Occupations, DOD Cooperative Research and Development Project Workers, and Fashion Models | USCIS 2022).

[50] It should be noted that any mention of the H1B visa in this dissertation, is really a reference to the Labor Application (LCA), an application filed by employers on behalf of the workers applying for work authorization for non-immigrant status (Labor Condition Application (LCA) Specialty Occupations with the H-1B, H-1B1 and E-3 Programs | Flag.dol.gov n.d.). The LCA in fact includes three different types of visas: the aforementioned H-1B, the H-1B1 visas (a variant of the H-1B for citizens of Singapore and Chile), and the E-3 (a variant of the H-1B visa for citizens of Australia) (Labor Condition Application (LCA) Specialty Occupations with the H-1B, H-1B1 and E-3 Programs | Flag.dol.gov n.d.). Because the majority of LCA visas are H-1B, rather than refer to the LCA I will simply allude to H-1B category in a broad sense. I.e., when describing data on H-1B visas in this dissertation, I am in fact counting data on H-1B, H-1B1, and E-3 as a single unit.

[51] The H-2A program allows U.S. employers or agents to bring in foreign-nationals to fill temporary agricultural jobs (H-2A Temporary Agricultural Workers | USCIS 2022).

[52] The H-2B program allows U.S. employers and agents to bring foreign nationals to fill temporary nonagricultural jobs (H-2B Temporary Non-Agricultural Workers | USCIS 2021).

[53] Labor certification is an immigration process through which a U.S. employer can hire a foreign worker permanently. Because a foreign employee can obtain a permanent position, the Labor Certification is often, although not always, regarded as the first step for a foreign worker to obtain an employment based Green Card (i.e., permanent residence) Green Card Application Process | International Center." n.d.). The Program

comes to measuring firms' preferences, (Facchinni et al. 2013; Lin 2019). This is because historically firms have been instrumental players in shaping U.S. immigration policy assisting with the creation of certain temporary work visas and annual cap of foreign-born workers (Facchini, Mayda, and Mishra 2011; Hanson 2010; Hatton and Williamson 2005; Kerr et al. 2015).

As discussed in Chapter 5, among the top specific-issues listed by immigration lobbying firms we find reference to improving the process of or expanding the number of H-type visas. We can appreciate that firms have, and continue, to play an integral role in the development of policies surrounding permits like H-1B, H-2A, and H-2B, including who qualifies to obtain one of these permits, how long a foreign-born worker can stay in the US with a given permit, and whether the employer can apply to renew an employees work permit (Facchini, Mayda, and Mishra 2011). In addition, individuals who possess temporary work permits like H-1B, H-2A, and H-2B can eventually apply to obtain a Permanent Labor Certification like PERM, which would eventually permit these same individuals to obtain permanent residence in the United States. However, obtaining an H-1B, H-2A, or H-2B visa is neither a requirement nor a guarantee that an individual will be granted permanent residence (H-1B to Green Card: The Definitive Guide to Process, Steps & Timeline n.d; PLLC 2021).

To obtain H-1B, H-2A, or H-2B visas, an employer must first submit a formal request to the Department of Labor (DOL) to obtain a foreign labor certification (About Foreign

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Electronic Review Management (PERM) was designed by the U.S. government to shorten the labor certification process time from years to just months (Program Electronic Review Management (PERM) Labor Certification 2020).

Labor Certification n.d.). [54] In essence, an employer must demonstrate that the reason they request to hire a foreign-born employee is because: a) it is in the interest of the employer to fill a specific position with a worker, and b) the position in question has been open to, yet unfilled by a US citizen or US National (Fact Sheet #26: Section H-2A of the Immigration and Nationality Act (INA) 2010; Fact Sheet #62O: Must an H-1B employer recruit U.S. workers before seeking H-1B workers? 2009; H-2B Visas: The Complex Process for Nonagricultural Employers to Hire Guest Workers | Cato Institute 2021).

By contrast, for other worker-visa categories like L, O, P, Q, or TN type visas (see Appendix Table A-4 for more information), employers are not required to obtain a foreign labor certification. In the case of L visas, the firm is simply requesting to transfer a foreign employee to work in the United States. In the case of O and P visas, we see that these visas are issued only to individuals possessing specific talents, like actors and athletes, while Q visas are issued to religious workers. In other words, while L, O, and P visas may signal the firms interest or their reliance on specific types of foreign workers, these firms do not need to go through the same rigorous verification process to obtain these permits for their workers as they do when it comes to H type visas. Lastly, TN status or TN visas are a special non-immigrant permits that are granted only to citizens of Canada or Mexico as a result of a NAFTA provision.

[54] In order to hire a foreign-born worker on temporary (H-1B, H-2A, or H-2B) or permanent basis (PERM), an employer must first apply and obtain a Labor Certification from the Department of Labor (DOL) (Program and FLAG Resources | U.S. Department of Labor n.d.). According to the DOL, to obtain a certification an employer must demonstrate that there are insufficient qualified U.S. workers available and willing to perform the work at wages that meet or exceed the prevailing wage pad for the occupation in question, in the area intended for employment (for more information see Program and FLAG Resources | U.S. Department of Labor n.d.).

It should also be noted that there is no numeric limit on the number of L, O, P, or TN[55] visas (Gelatt 2019; P Visa | Immigration Solutions n.d.). By contrast, H-1B visas are capped at 85,000 visas per year (although renewals do not count against the cap nor do those H-1B visas that are sponsored by a college, university, or nonprofit). There is also a cap on the number of H-2B visas at 66,000 per year, though Congress has recently allowed Homeland Security to increase the cap if it is assessed that there is a need for more workers (Gelatt 2019). There is no numeric cap on H-2A visas.

In fact, the majority of temporary working visas tend to be H-type visas. Between 2014 and 2018, the average number of H-1B visas issued was about 170,000 (not counting H1B1 or E3 visas). The average number of H-2A visas was about 138,000 and the number of H-2B was about 79,000 in that same time period (Gelatt 2019). Given that firms must take an extra step in order to secure employees' visas as well as the PERM, a closer look at the number of H-type visas and PERM that a firm obtains in a given year provides an important signal, and will be the central focus of our following analysis. A high number of visa requests, signals that the firm in question has a strong preference for a given type of foreign worker, strong enough that they are willing to invest and commit themselves to expend resources to obtain said worker, even under the prospect that said worker's visa application could be denied by the DOL.

Admittedly, a firm's demand for foreign born workers may be due to other factors, some of which may be more ignoble. There is both concern and evidence to suggest that relying on foreign-born workers (whether documented or undocumented) is predicated on the

[55] Note that "The TN visa is not a dual intent visa, meaning that holders must show at the time of initial application and at each visa renewal that they do not intend to immigrate to the United States " (Kerr, Kerr, and Lincoln 2015a, 124).

fact that foreign workers are generally more complacent and likely to acquiesce to the demand of employers generally due to fear that failing to do so may jeopardize their status in the United States. In essence, by relying on foreign born workers, firms may be more likely to exploit their labor force than they would were they instead relying on U.S. nationals (03-17-15 Grassley Statement1.pdf (senate.gov); Senators Raise Concerns Over H-2B Visa Abuses That Enable Exploitation | United States Senate Committee on the Judiciary; Ripe for Reform: Abuse of Agricultural Workers in the H-2A Visa Program - Centro de los Derechos del Migrante, Inc. (cdmigrante.org)). Hence, the incentive to expand resources to hire foreign born workers may be in large part influenced by firms' desires to employ a complacent and submissive workforce.

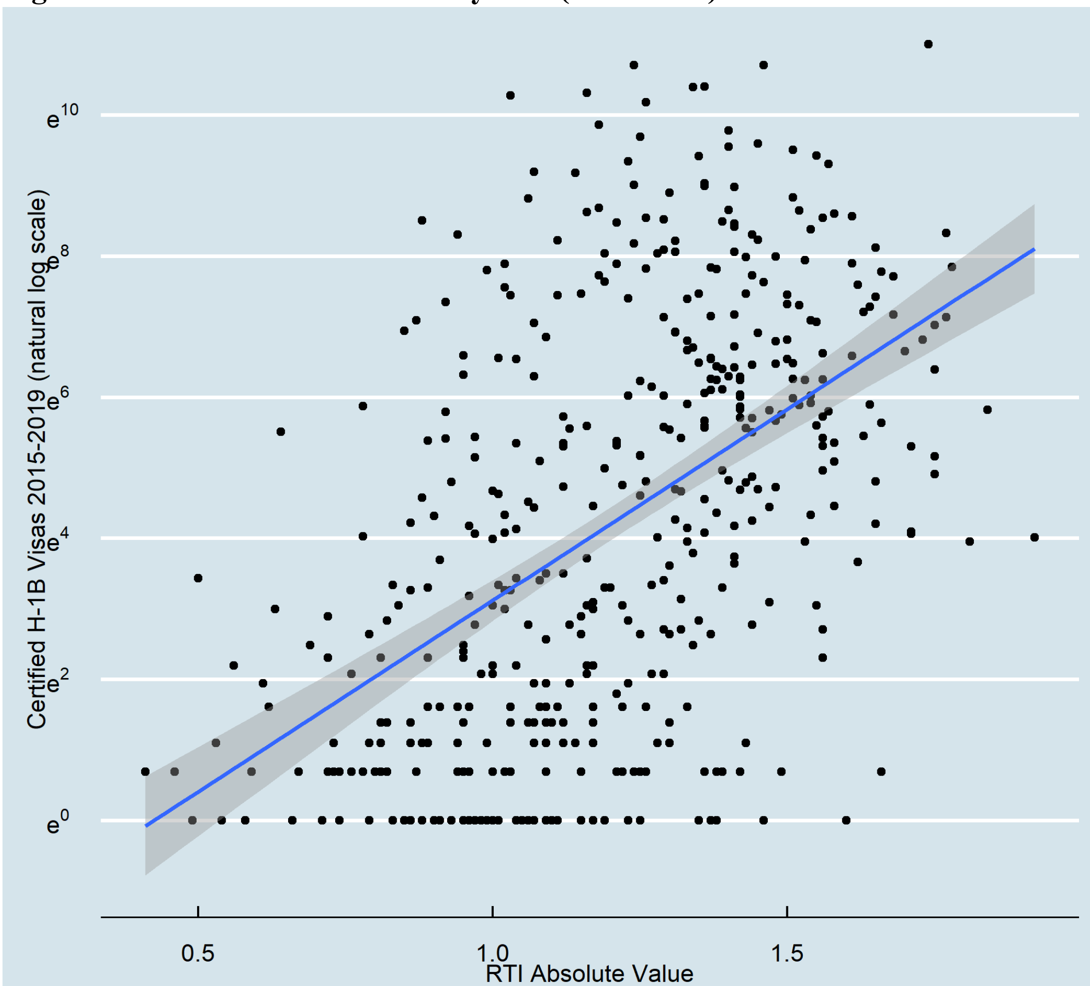
However, whether a firm seeks to hire foreign workers in order to benefit from their exploitation or not, is not antithetical to this project (i.e., does automation impact firms' immigration policy preferences). Even if firms are driven to rely on foreign workers in order to exploit them, we can see that: a) not all firms rely on foreign workers and b) not all firms lobby for foreign workers. Thus, we could ask whether automation prompts some firms to lobby for immigration, even if the motive behind those firms' lobbying stems from a desire to continue relying on a docile workforce. In other words, whether automation increases firms' policy preferences for some firms may very well be due to the fact that those preferences for foreign workers are initially derived from obtaining a compliant workforce.

One thing to note, though, is that a focus on H-type visas and PERM may overlook other types of foreign workers that firms rely upon, especially undocumented workers. Yet, even if we are over-looking data on all types of foreign-born workers, this should not necessarily be seen as a liability or impediment. If anything, firm-level data revealing the number of temporary foreign-born workers (e.g., those workers who require a worker visa) can reveal, to a large extent, the composition of foreign-born workers employed by firms within a given year. Additionally, by looking at the number of temporary foreign-born workers (i.e., requiring a visa) we can also obtain a sense of firms-immigration policy preferences, since firms must apply to the Federal Government to obtain temporary worker visas, as well as Permanent Labor Certifications (PERM) (Facchini, Mayda, and Mishra 2011).

7.3 How "Routine" are Foreign Workers (RTI and Foreign Work Permits)

Consider, now, figures 7-1, 7-2, 7-3, and 7-4. The figures suggest that in general, more temporary work visas as well as the PERM are on average given to non-routine occupations. The only exception we found was the case of H-2B visas where it appears that fewer visas are issued to non-routine occupations. To create these figures, I relied on data from the DOL's Office of Foreign Labor Certification (OFLC) Performance Data (Program and FLAG Resources | U.S. Department of Labor n.d.; Performance Data | U.S. Department of Labor n.d.). The benefit of the DOL's OFLC Performance data is that it provides comprehensive data on the number of requested H-type visas and PERM in a given year—including which requests were certified versus which requests were denied—as well as who were the employers requesting these visas. For example, how many requests for H-1B visas were made by Microsoft and Amazon and the name and description (including the SOC-Code) of the occupation of the employee (Performance Data | U.S. Department of Labor n.d.). Because the DOL's OFLC Performance data contained information on the SOC-Code of those workers who had been issued an H-type visa or PERM in a given year, it is possible to combine this information with the RTI, given that RTI was made using O*NET 26.0 data, which also utilizes the SOC classification system to evaluate occupations.

Figure 7-1: Certified H-1B Visas by RTI (2015-2019):

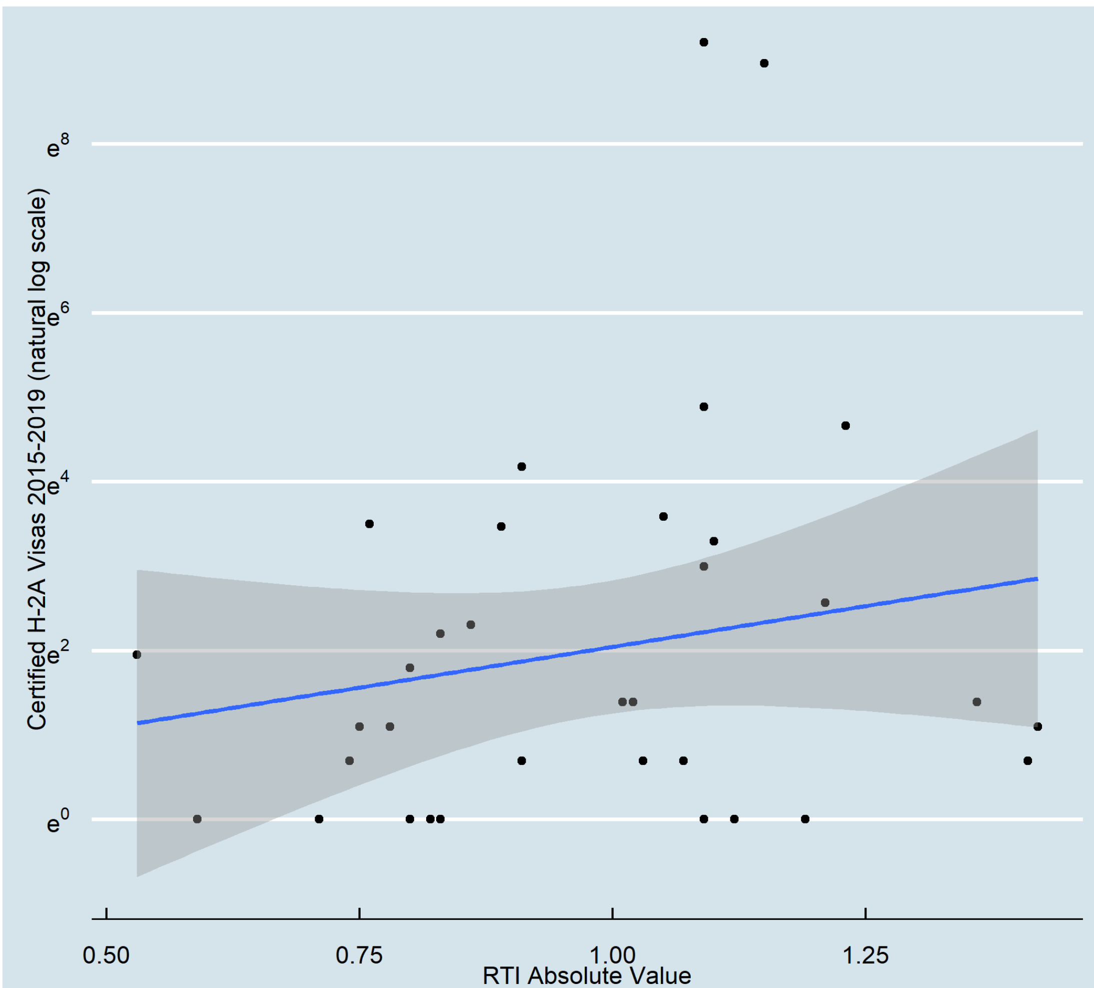


Source:https://www.dol.gov/agencies/eta/foreign-labor/performance

For example, the occupation Management Analyst (SOC-Code 13-1111) was the occupation that obtained the greatest number of certified H-1B visas between 2015 and 2019 (a total of 59,9897 certified visas). The RTI score for this occupation was 1.74, meaning it was an occupation that could be considered non-routine per the RTI criteria. By contrast, the occupation Ophthalmic Laboratory Technician (51-9083), with an RTI score of 0.49, was issued only one certified H-1B visa between 2015 and 2019.

One challenge that arose when accessing the DOL's OFLC Performance data was its inconsistency with the recording of SOC-Codes. For example, some employers would use different SOC-Codes to label the same occupation, while in other cases the same SOC-Code would be used to label different occupations. Such inconsistencies mean that it was not always possible to identify and track all occupations that had been issued a certified H-type visa or PERM, with their corresponding RTI score.

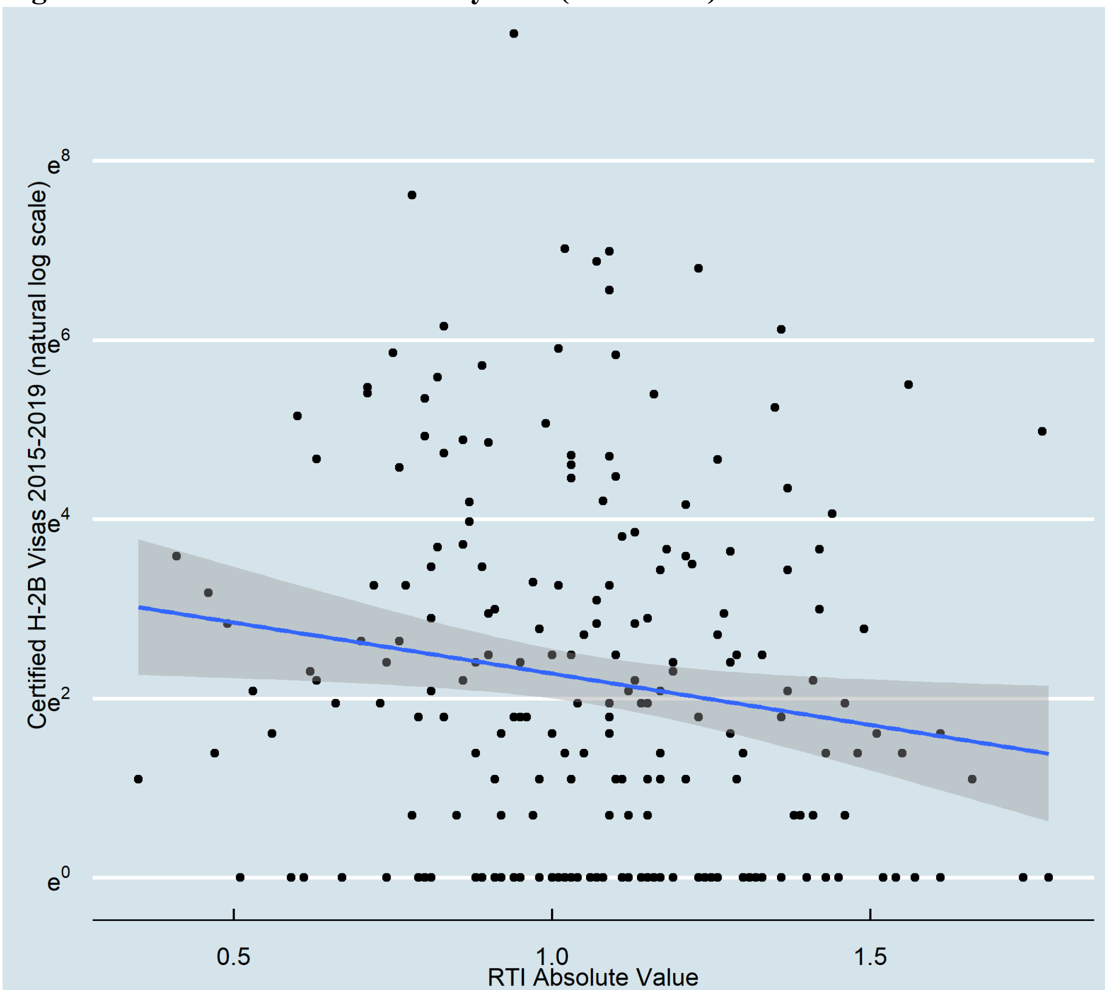
Figure 7-2: Certified H-2A Visas by RTI (2015-2019)



Source: https://www.dol.gov/agencies/eta/foreign-labor/performance

We can appreciate thus, in Figure 7-1, a positive trend. The higher the absolute value of an SOC-Occupation's RTI score, the more likely it is for this occupation to obtain an H-1B visa, when looking at the number of H-1B visas issued to 458 SOC-occupations between 2015 and 2019.

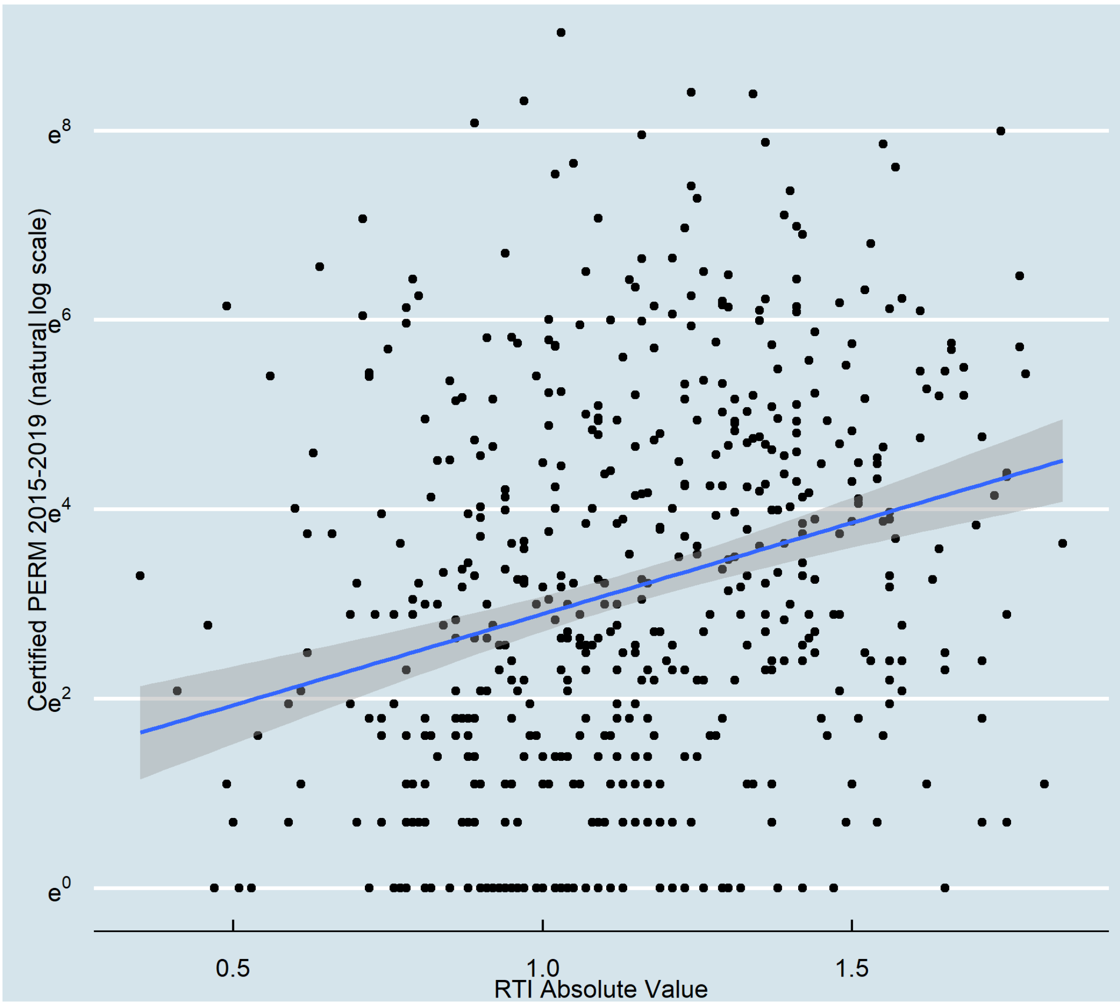
Figure 7-3: Certified H-2B Visas by RTI (2015-2019)



Source: https://www.dol.gov/agencies/eta/foreign-labor/performance

There also appears to be a positive correlation between occupations that are less routine, or more non-routine, and H-2A visas. More H-2A visas are given to occupations with higher absolute values along the RTI index as can be seen in figure 7-2. In this case, though, we are speaking only of 35 SOC-Occupations between 2015 and 2019. One thing to highlight is that H2A visas are by design issued to individuals working in agricultural occupations. Hence it makes sense that our observations be based on fewer occupations (H-2A Temporary Agricultural Workers | USCIS 2022).

Figure 7-4: Certified PERM by RTI (2015-2019)



Source: https://www.dol.gov/agencies/eta/foreign-labor/performance

In the case of H2B Visas there seems to be an inverse relationship whereby the less routine an occupation or the more non-routine this same occupation is, the fewer H2B visas said occupation gets, as can be seen in figure 7-3. This is for 209 occupations issued H2B Visas between 2015 and 2019 (it could be that H2B visas wind up being given to more routine occupations by design). Lastly, in the case of PERM, it appears that there is a positive correlation between the less routine an occupation is (i.e., the more non-routine it is) and the more likely it is for said occupation to obtain a PERM. This can be observed in figure 7-4, on the basis of 542 SOC-Occupations issued PERM between 2015 and 2019.

Overall, the more non-routine an occupation is, the more likely this occupation will be issue an H-type visa or PERM (except for the H-2B). While we cannot yet make a causal claim, as there may be some omitted variable that could explain why more non-routine occupations have gotten more visas in the past, there does appear to be a pattern whereby more non-routine occupations are issued H type visas.

7.4. Salience vs Access: The Challenge

In 2015, the German engineer and economist Klaus Schwab, executive chairman of the World Economic Forum, stated that the world was in the midst of witnessing a transition into a "fourth industrial revolution," characterized by emerging technology breakthroughs like artificial intelligence (AI), robotics, autonomous vehicles, 3D printing and more (Schwab 2015, 7). Even if neo-classical economics has historically asserted that advances in technology are necessary and desirable for enhancing productivity, economic growth, and living standards, currently many economists have called attention to the fact that as a society we are, "flying blind" in terms of our understanding of technology's human and social costs (Mitchell and Brynjolfsson 2017; Zolas et al. 2020). There is profound uncertainty and apprehension about the psycho-social, economic, and political consequences that these new technologies could have worldwide (Schwab 2015, 8).

There are two main reasons why there is such uncertainty. First, the high rate at which new technologies are developed and released has made it difficult for policy makers, scholars, and civil servants, to track and therefore understand the magnitude and impact these technologies have had in general, whether it is on labor, economically, or socially (Schwab

2015, 8-9). At the same time, there has not yet been a comprehensive effort to track the adoption of specific new technologies (e.g., robotics) along with questions of productivity and labor size at the firm-level (Zolas et al. 2020).

To be clear, the issue is not that there is *no* data on firm-level technology adoption. Instead, we can think of the problem as having more to do with the fact that so far, little priority has been given to developing a comprehensive database that tracks firm technology adoption and its impacts on production and labor (GAO 2019; Stokey 2021; Zolas et al. 2020). Existing data are either limited in their scope (e.g., some surveys track the adoption of specific machinery like robotics among manufacturing firms only), provide information for only a brief period in time (e.g., data on technology adoption among firms for one year only), has been discontinued, or provide aggregate-level data only (i.e., technology-adoption at the industry or economic sector level instead of firm-level data) (GAO 2019; Stokey 2021; Zolas et al. 2020).

Understanding that we face data limitations presents certain challenges given the fact that it is not possible to fully track firm-adoption rates and the use of technology in conjunction with information on the type of workers firms employ. That we cannot see the rate at which specific firms adopt certain technologies for example, prevents us from fully testing whether for some specific firms, automation or technology adoption is correlated with trends in that same firms' lobbying or reliance on foreign workers.

7.4.1 The Annual Business Survey

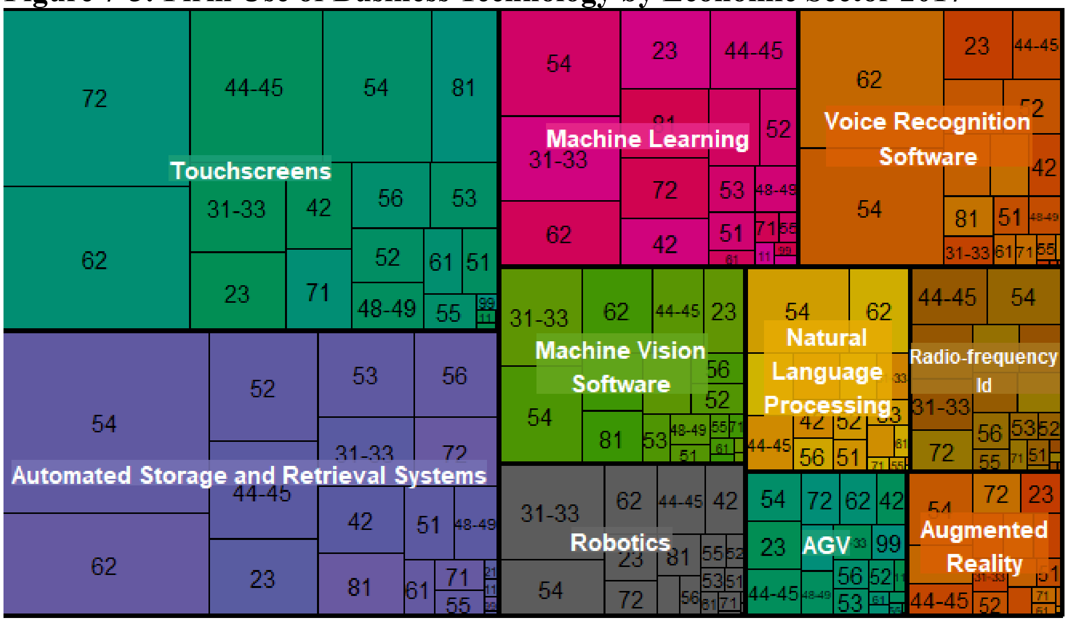
Several recent efforts have been made, both within the United States as well as globally, to keep better track of firm-level adoption and implementation of new technologies. For example, the European Commission has produced an enterprise-level survey looking at the adoption of different AI technologies by businesses (European Commission, Directorate-General for Communications Networks, Content and Technology 2020). Similarly, Statistics Canada has carried out firm-level data collection on the adoption of different technologies, like robots (Dixon, Hong, and Wu 2021). Even international organizations like the United Nations (UN) have begun the development of a country-level database tracking robot imports via the UN International Trade Statistics Database (COMTRADE).

In the United States, the purpose of the Census Bureau's Annual Business Survey (ABS)[56], is to provide information on selected economic and demographic characteristics of businesses (U.S. Census Bureau n.d.). Among these business characteristics, we find that the ABS collects information on the adoption and use of several advanced technologies on an annual basis, from randomly selected nationally represented sample of firms (Zolas et al. 2020, 2).[57] The benefit of the ABS is that we have for the first time an effort to survey and track, longitudinally, economic questions like how much companies spend on research and development (R&D) for new technologies, as well as questions regarding the adoption rates of different technologies, e.g., AI, robotics, and automated guided vehicles (AGV) (U.S. Census Bureau n.d.). For more information on the technologies surveyed, see appendix table A-6 and A-7. The ABS differs from previous and existing surveys looking at technology adoption at the firm-level in the following ways: a) its scope is not limited to measuring the implementation of a single or small number of technologies, b) the ABS aims to add different measures on technology adoption on a yearly basis, and c) it randomly selects businesses to survey that are representative of the national economy. Because the ABS surveys firms

[56] The ABS is conducted by the U.S. Census Bureau and the National Center for Science and Engineering and Statistic, which is part of the National Science Foundation (U.S. Census Bureau n.d.).
[57] The ABS surveys all private non-farm sectors of the economy (Zolas et al. 2020).

directly, we are able to address questions like the extent to which individual firms adopt and use different technologies, the number of employees working for firms within a given year, and how much the use of new technologies contributes to firms' revenues in a given year.

Figure 7-5: Firm Use of Business Technology by Economic Sector 2017



Source https://www.census.gov/data/tables/2018/econ/abs/2018-abs-company-summary.html

Figures 7-5 and 7-6 provide a treemap summarizing the use of specific business technologies in each NAICS economic sector. The treemaps are separated by color to indicate the use of a specific business technology by firms. Each rectangle within each colored box represents the total number of firms that responded in each survey that they had used the given technology for the purpose of producing a good or service. For example, when looking at the technology *Automated Storage Retrieval System*[58] (the blue box on the bottom-left corner of figure 7-5) we can see that the largest rectangle in this box corresponds to economic sector 54 (Professional, Scientific, and Technical Services). To be exact, in this

[58] Automated storage and retrieval system, sometimes referred to as ASRS or AS/RS, refers to a variety of computer-controlled systems for that can automatically place and retrieve loads from defined storage locations, with precision, accuracy, and speed (Automated Storage and Retrieval Systems (mhi.org)).

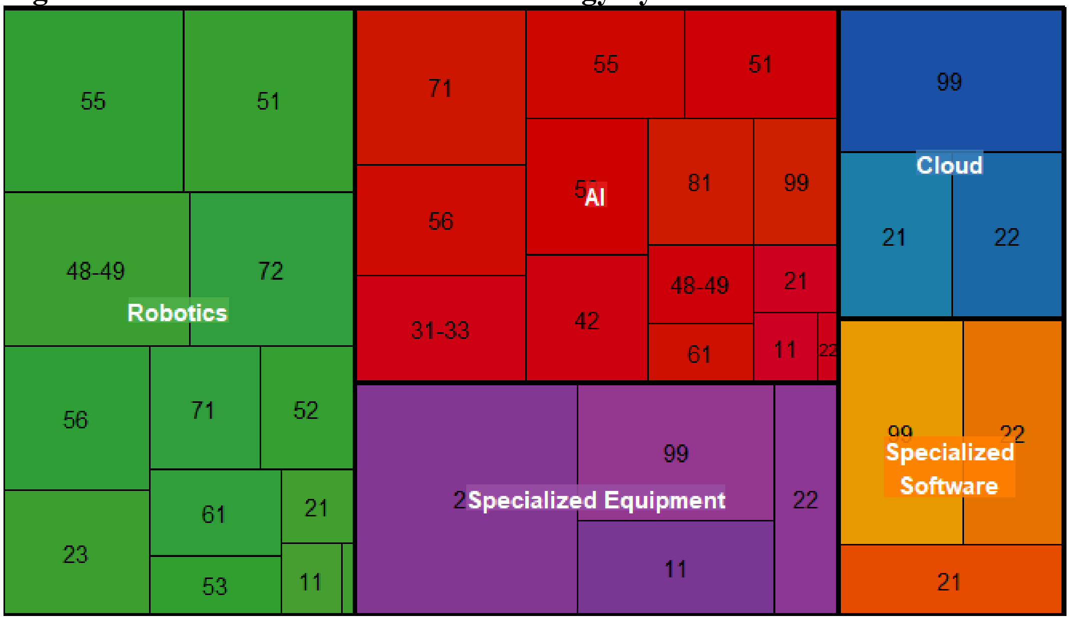
case 53,903 surveyed firms within economic sector 54 reported to have used *Automated Storage Retrieval System* for the purpose of producing a good or service.

I produced Figure 7-5 using information on ABS 2017's *Table 3A: Business Technologies by 3-Digit NAICS for the United States*[59], which contained information on approximately 850,000 surveyed employer businesses, including the listing and extent of their reliance on business technologies to meet their production needs (U.S. Census Bureau. 2018a; U.S. Census Bureau. 2018b). Similarly, to create Figure 7-6, I relied on the 2018 ABS table titled, *Extent of Technology Use of Employer by 2-difit NAICS for the United States*, depicting similar information (albeit on different business technologies (except for robotics), this time based on data derived from 300,000 employer surveyed businesses (U.S. Census Bureau 2019; U.S. Census Bureau 2018b).[60]

[59] It should be noted that *Table 3A: Business Technologies by 3-Digit NAICS for the United States*, features information on business use of technology collected in 2017 but published in 2018. The census refers to this table as part of the 2018 ABS data (given its publication year) despite the fact that it contains information on data collected in 2017. In this dissertation, I will thus refer to 2017 data when referencing ABS information published as part of their 2018 survey.

[60] Similarly, the *Extent of Technology Use of Employer by 2-difit NAICS for the United States* table is listed as part of the 2019 ABS -- Technology Characteristics of Business data. In this dissertation, I will refer to 2018 data when referencing information from ABS data published in 2019.

Figure 7-6: Firm Use of Business Technology by Economic Sector 2018



Source: https://www.census.gov/programs-surveys/abs/data/tables.2019.List_1428666720.html#list-tab-List_1428666720

For the 2017 survey, firms were asked the following question, "In 2017, to what extent did this business use the following technologies in producing goods or services?".[61] Surveyed firms were given a list of 10 different business technologies (as can be seen of figure 7-5) and asked to mark their reliance on a given business technology to meet their production needs. In Appendix Figure A-1, I put a copy of this question along with the different options that respondents had to answer.

To construct Figure 7-5, I began first by identifying and counting the total number of firms by economic sector that had indicated the use of a listed business technology in their production or service. This did not take into consideration the degree to which a firm had relied on a given business technology (e.g., did robotics account for 5%, 25%, or over 25% of their production of a good or service). The point was simply to see how many firms within

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[61] For more information, please see: https://www2.census.gov/programs-surveys/abs/information/2018/abs_2018.pdf.

a given economic sector had used a given business technology to meet their production needs.

In the case of the 2018 survey, sampled firmed were asked, "During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?"[62] Surveyed firms were given a list of five different business technologies (as can be seen of figure 7-6) and asked to mark their reliance on a given business technology to meet their production needs. In Appendix 1, figure A-2 there is a copy of this question along with the different options that respondents had to answer.

Like with figure 7-5, to construct figure 7-6 I first counted all firms that indicated they had used a given technology to meet their production or service needs. Much like with figure 7-5, the point of figure 7-6 was not to differentiate whether a firm had listed "Low use, Moderate use, or High use," of robotics to meet their production needs, but simply look at any firms that had listed using the technology to meet their production needs.

Yet, despite the promise of the ABS, I identified a number of important limitations to this survey. Although the ABS surveys firms directly, it does not identify *which* firms they surveyed. Thus, the ABS can tell us the extent to which firms in economic sector 54 (Professional, Scientific, and Technical Services), for example, report having used technologies like machine learning, robotics, or automated vehicles (AGV) in their production of a goods or services in a 2017. However, what the ABS cannot tell us is the extent to which distinct firms in economic sector 54 (e.g., Microsoft or Oracle) rely on individual technologies (e.g., AI or robotics) to meet their production needs.

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[62] For more information, please see: https://www2.census.gov/programs-surveys/abs/information/abs_2019.pdf.

Thus, although we can identify the immigration lobbying activity, as well as the types of foreign workers of some firms, we are unable to determine the extent to which any of those same firms rely on technology to meet their production needs. All we can do with the existing data is observe the trends of firm technology adoption, lobbying, and reliance of foreign workers at the economic sector level. In other words, we can aggregate data from the firm-level to the economic sector-level and test for relationships between technology adoption, reliance on foreign workers, and lobbying by firms at the economic sector level.

The problem with aggregating from the firm to the economic sector is that it is highly unlikely that we will be able to observe any correspondence between the technology adoption and lobbying positions of an entire economic sector. This is because within any economic sector there will always be variance among the position of some firms vis-à-vis immigration, or any policy for that matter (Brulle 2018; Delmas, Lim and Nairn-Birch 2016).[63]

Another limitation we encounter is the fact that the ABS relies on Likert-like[64] psychometric item scoring schemes, when it comes to tracking and measuring firm reliance on new technologies as well as the types of productivity and labor outcomes derived by firms using a given technology. For example, in the 2018 ABS (which contained data collected for the year 2017), surveyed firms were asked questions like, "to what extend did this business use machine learning in producing goods or services." Respondents then had to choose one out of six options (no use, testing but not using in production or service, in use for less than

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[63] While some lobbying literature evaluates sector-level policy preferences (e.g., economic sectors' support for/opposition to policies restricting air pollution) (e.g., Delmas et al. 2016), for the purpose of analysis, it is much harder to analyze the question of immigration since a) there are no economic sectors in which economic activity revolves significantly around the reliance on immigrants and b) there is lobbying on immigration coming from all economic sectors.

[64] Likert-like refers to survey reliance on Likert scales. Likert scales feature across surveys, where respondents generally mark their level of agreement/disagreement with a given statement or question (Carifio and Perla 2007).

5% of production or service, in use for between 5-25% of production or service, in use for more than 25% of production or service, don't know).[65] [66]

However, there is no indication of what exactly is meant by business technology accounting for 5% of production needs, or for 25% for that matter. Thus, although firms can disclose whether they are using certain technologies to meet their production needs, we cannot get an accurate estimate of how significant the use of that given technology is for a firm's production needs. This seeming arbitrariness becomes even more apparent when we observe the 2019 ABS (containing data collected in 2018). As can be seen in appendix figure A-2, if a surveyed firm had relied on a given technology to meet its production needs, when asked to what extent said technology was used, the firm in question was asked to select one of the following options: low use, moderate use, or high use.[67]

Lastly, the ABS is a relatively new survey. The first year for which we find available data is 2017 and the most recent year for which there is data (as of March 2022) is 2019.[68] Thus, there are only three years' worth of data currently available. In addition, the content of each survey changes for each of the three years. For example, in 2017 about 850,000 randomly selected businesses were surveyed, while in 2018 that number decreased to 300,000 (Zolas et al. 2020, 4-5). Moreover, with the exception of robotics, sampled firms

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[65] Note: because Likert scales are non-parametric, i.e., they are sampled statistics in which the true distribution of the population is either unknown or not assumed explicitly, the scale measurements tend to be regarded as ordinal and thus unable to be used statistical measurement that assumes samples are derived from normally distributed data (i.e., parametric data) that do not assume an explicit distribution f we tend to not use measurements like mean and median use things like ordinal regression and chi-square test (see here for more information) (Bishop and Herron 2015).

[66] For more information please see: https://www2.census.gov/programs-surveys/abs/information/2018/abs_2018.pdf

[67] For more information please see: https://www2.census.gov/programs-surveys/abs/information/abs_2019.pdf

[68] There are plans to conduct the ABS for five years rotating modules on different topics, thereby permitting ABS data to be used longitudinal analysis (Zolas et al. 2020, 4). However, presently (February 2022), data depicting technology use by firms is available only for the years 2017 and 2018.

were surveyed on their reliance of different business technologies in the 2017 and 2018 surveys (see appendix tables A-6 and A-7).

7.5. Working with the Existing Data

Much of the literature that looks at firms' immigration lobbying (e.g., Facchini, Mayda, and Mishra 2011; Kerr, Lincoln, and Mishra 2014) or lobbying on other political issues (Brulle 2018; Delmas, Lim and Nairn-Birch 2016) tends to look at the lobbying activity of firms over time. Longitudinal analysis of firm lobbying is useful to look for changes and continuity among lobbying-firms, while also accounting for variation in questions like the state of the economy or the political-institutional context of a given period of time (Aizenberg and Hanegraaff 2022; Box-Steffensmeier, Christenson, and Hitt 2013; Naoi and Krauss 2009).[69]

Yet, the data collected by the 2018 and the 2017 ABS can be treated as different cross-sectional surveys, in addition to constituting information for only two years, cannot really be treated as panel data, given that the same size of surveyed firms, along with the surveys itself change. While it would be conceivable to regard these two samples as part of a longitudinal study, where we could relax the assumption that the same firms are being surveyed, the second problem comes from the fact that the questions also change. In short,

[69] While cross-section data refers to observations made of specific units from a target population (e.g., firms in our case) at one point in time (Gujarati and Porter 2009, 22), by contrast, longitudinal data entails the repeated observations of the same units from a target population across time (Gujarati and Porter 2009, 23). While it may be more difficult to collect longitudinal data due to issues of attrition and costs, longitudinal data is seen as a useful step towards establishing a causal relationship between an independent and dependent variable, since reiterated observations on the same variables are more amenable for the control of confounding or omitted variables that may threaten inference (Morin, Olsson, and Atikcan 2021, 73). Because we are observing the same units across time with longitudinal analysis, we can measure or account for any the difference between those units that are derived from a situation in which some of those units are exposed to a "treatment" and other units are not, with a higher degree of confidence, given our multiple observation (Jennings and Niemi 1975).

the two surveys measure different things as it pertains to the use of different business technologies by economic sector.

Given these differences between surveys, the one estimation model we can use to test the relationship between technology adoption and immigration lobbying by sector is pooled OLS.[70] Pooled data, unlike panel or longitudinal data, merely consists of a combination of different cross-sectional data where different units of observation are sampled (Gujarati and Porter 2009, 23).

Table 7-1: Immigration Lobbying and Robotics

	Number of Immigration Reports
Firm Use of Robotics	0.003
	(0.004)
Constant	111.326***
	(24.343)
N	38
R^2	0.019
Adjusted R^2	-0.009
F Statistic	0.688 (df = 1; 36)

*p < .1; **p < .05; ***p < .01

However, while the use of pooled OLS permits us to derive an estimate between robotics and lobbying, by economic sector, the results shown on Table 7-1 are very weak. Table 7-1 shows the relationship between robotic use (measured as the total number of firms that reported to have used robotics to meet their production needs within each economic sector), and immigration lobbying (measured as the total number of firms/trade associations that listed immigration in their lobbying reports), for the years 2017 and 2018 as part of a

[70] The difference between pooled OLS and fixed effects is that the former often relies on a collection of pooled cross sections. Pooled data unlike panel or longitudinal data, merely consists of a combination of different cross-sectional data where different units of observation are sampled (Gujarati and Porter 2009, 23).

pooled OLS model. However, as can be seen in table 7-1, the bivariate relationship between robotic use and immigration-lobbying activity for 2017 and 2018 is close to 0. This means that for every additional use of robotics to meet the production needs of firms, we can expect an increase of 0.003 in the listings of immigration within a lobbying report.

A few things to keep in mind. First, our account of robotics is simply whether a firm responded yes in the 2017 and 2018 survey to the use of robotics. There were different levels being specified (5%,10%,25%) and (Low, Mid, and High use) in the 2017 and 2018 surveys respectively. Second the 2018 survey question asked whether the firm had used robotics in the last three years (2016,2017, and 2018). Still, if we make things as binary then there should be no problem because we could say of all randomly selected firms in a given economic sector how many responded affirmatively to the use of robotics (i.e., we simply counted the number of firms that reported to have used a given business technology to meet its production needs without differentiating on the extent to which robotics had been used to meet a surveyed firms' production needs (i.e., not accounting for whether firms had reported 5% or 25% or High versus Low but simply that they had reported to have used robotics to meet their production needs)

Yet, even if we relax our metrics and simply look for the correlation between robotics use and immigration lobbying by sector, our regression coefficient is close to 0, likely due to the large variance we would see across economic sectors, with no statistical significance and magnitude close to 0. As discussed in previous chapters, larger firms tend to be more active in lobbying than smaller ones. Furthermore, two years provides limited information on lobbying.

Table 7-2 summarizes the pooled OLS model, involving the relationship between use of robotics (measured as the total number of firms that reported to have used robotics to meet their production needs) and the number of certified H-type visas (columns 1-3) and PERM (column 4) issued between 2017 and 2018.

Although Figure 7-2 no longer reveals information on lobbying, it does provides an interesting insight as it pertains to the relationship between robotics use and foreign workers. In this case, we see a positive relationship between the use of robotics and certified H1B type visas, where for every additional use of robotics, there is a corresponding increase of close to 8 units of certified H1B type visas, at statistically significant levels. However, the R-squared (goodness of fit) in the case of column 1 is of 0.225[71], suggesting a weak correlation between these variables.

Table 7-2: Firm Robotics Use and Certified Work Permits for Foreign Workers

	Certified H1B (1)	Certified H2A (2)	Certified H2B (3)	Certified PERM (4)
Firm Use of Robotics	7.776***	-0.099	-0.009	0.747***
	(2.404)	(0.082)	(0.022)	(0.145)
Constant	-432.841	1,091.571*	392.168**	119.398
	(14,992.330)	(573.219)	(146.990)	(906.181)
N	38	27	34	38
R^2	0.225	0.055	0.005	0.423
Adjusted R^2	0.204	0.017	-0.026	0.407
F Statistic	10.460*** (df = 1; 36)	1.443 (df = 1; 25)	0.166 (df = 1; 32)	26.432*** (df = 1; 36)

*p < .1; **p < .05; ***p < .01

Moreover, in the case of robotics and H-2A and H2-B visas, as seen in columns 2 and 3, we see an inverse relationship between robotics use and certified H-2A and H-2B visas

[71] Normally, relationship between variables is said to be weak when the value of r-squared is $0.3<R^2<0.5$ (Wooldridge 2013; 844).

that contravenes our expectation. However, in both cases, the relationship is close to 0, and not statistically significant. This may very well be because H-2A visas tend to be issued to agricultural workers. It does appear that an increase in robotics slightly increases the number of Sector 11 workers.[72] In the case of robotics and H-2B visas, as seen in column 3, we see that there is a negative relationship between firm reliance on robotics and the number of certified H-2B visas issued. This relationship is also close to 0 and not statistically significant. Lastly when it comes to robotics and PERM there appears to be a statistically significant relationship between robotics use by firms per economic sector and the number of certified PERM issued to firms by economic sector, as seen in column 4. However, the effect appears to be close to 0. I.e., for every additional unit increase in use of robotics there is a corresponding increase of about 0.7 units in certified PERM issued.

7.6. Discussion

Despite the null findings, some encouraging insights may have been uncovered. To start, we do witness the causal arrow pointing in a direction that was similar to our initial claim. Given the logic of task-based models, we can appreciate a positive correlation, in which increasingly, more worker permits like H-type visas are going to foreign workers working in non-routine occupations, as can be seen with H-1B and H-2A visas, as well as PERM (with the exception of H-2B visas where more visas are seemingly going to more routine occupations). Without succumbing to the fallacy of correlation entails causation, this dissertation proposes that more work could be done to further elucidate why it is that more H-1B, H-2A, and PERM are going to foreign born workers working in non-routine

[72] As ABS surveys all non-farm employer businesses (About (census.gov)) we may be overlooking the effects of robotics use on economic sector 11, given that we do not have information on farming firms' usage of robotics.

occupations, and whether this increase in the number of foreign-born workers in non-routine occupations is caused by the qualified effects of automation on labor (i.e., *complementary and additive* effects), or whether it is due to something else. It is also worth further scrutinizing, why in the case of H-2B visas we see the reverse, i.e., more visas being issued to routine occupations.

It is also worth highlighting that one of the main challenges encountered was the limitation of existing data. While there is growing interest in better tracking the impact of technology adoption on labor, we are still missing a comprehensive database that can identify at the very least individual-firm adoptions of technology. Without accounting for how individual firms use new technology to meet their production needs any analysis involving the effects of technology on labor, including immigrant labor (be it the number of foreign workers employed by firms, or the extent to which firms lobby on the issue of immigration) entails an aggregate level analysis which will be broad and probably not very accurate.

However, initiatives like ABS show that there is room for growth. For one, should there be more annual surveys on business technology information, perhaps we may get more information on the usage of the same technology, albeit in different time periods, enabling longitudinal analysis on the impact of certain business technologies. Lastly, there is an opportunity to rely more information about individual firm-reliance on business technologies. Much like the Center for Responsive Politics tracks information on firm and trade association lobbying, more data could be collected as it pertains to firm-level technology adoption. It is likely that initially, such a database would feature information from larger firms, thus overlooking the technology adoption of mid-size and smaller firms, and while this may give us a partial account of what is happening, regarding the impact of technology on labor, this may very well be an important first step to ensure we don't continue "flying blind."

CHAPTER 8. EMPRICAL TESTS—FIXED EFFECTS

Initiatives like the U.S. Census Annual Business Survey (ABS) represent an important step in the collection and analysis of data involving the implementation of new business technologies (like robotics and machine learning) to meet firms' production needs. However, one critical limitation of the ABS data is the fact that it is not possible to differentiate individual firms' use of business technologies. In other words, although the ABS surveys different firms, data on production is presented (by the ABS) at the aggregate level. We can see the number of firms using a given technology (e.g., robotics) at the level of economic sector, for example, but we cannot differentiate which firms are the ones using the technology in question.

The inability to identify technology adoption at the firm level becomes an issue because, industry and sector-level data is likely going to be leveraged by larger firms, which are more likely to spend both on technology to meet their production needs as they are on lobbying (Jensen, Quinn, and Weymouth 2015; Maderia 2016; Osgood 2017). Thus, it is critical to differentiate not only how individual firms lobby but also how they rely on different business technologies to meet their production needs.

Given that the ABS data does not permit for firm differentiation involving their respective adoption and use of business technologies to meet their production needs, the need for an alternative source of data becomes necessary, a source that permits us to look and identify firm-level technology use. One such alternative is Refinitiv Eikon, a set of software products that allow access to market data on firms including on indicators like foreign exchange, money market, and funds, among others. Unlike with the ABS, Eikon permits us to look at different indicators by individual firms (e.g., look at the employment and capital spending of companies like Microsoft and Amazon). However, unlike the ABS, with Eikon it is not possible to gauge how specific business technologies are adopted and used to meet production needs (e.g., how do Microsoft or Amazon rely on robotics or machine learning to meet their production needs).

In this section, I discuss my findings involving data from numerous sources including Eikon. I test the link between firms' capital expenditures' (as a proxy for automation) and its effect on firm immigration lobbying expenditures. Relying on firm-level indicators reveals some positive and statistically significant findings in the way that automation impacts firm-level immigration lobbying. Although there are still some challenges that arise, namely that capital spending may be itself too broad and cannot differentiate individual technologies and their respective impact on firms' production needs, nonetheless this measure is more amenable to the type of longitudinal analysis involving firms.

8.1. Data and Data Analysis

Dependent Variable

For my dependent variable in this section, I looked at firms' annual immigration lobbying expenditures, as reported by the Center for Responsive Politics (CRP). To measure immigration lobbying activity, I looked at firms'[73] annual number of finalized[74] lobbying reports submitted to the SPOR that listed immigration as a lobbying issue and added the total amount of lobbying dispensed by the firm in question, as listed in the lobbying report. One important caveat to note is that the amount listed in the report, *should not* be interpreted as

[73] In my case, I looked at instances in which distinctive firms (e.g., Microsoft) were listed under the variable Client in the CRP database

[74] By finalized we mean a report that is submitted to SOPR indicating that it (the report) should be used to calculate the amount spent lobbying (For more information please see: https://www.opensecrets.org/federal-lobbying/methodology).

the amount a firm spent on immigration lobbying but rather how much a firm spent lobbying on political issues including immigration. As discussed in Chapter 4, large firms, especially those that lobby individually, often lobby for multiple issues at the same time, i.e., a company will lobby on issues like taxation, immigration, and environmental regulation at the same time. Thus, unless the only lobbying issue listed in a report is immigration, we cannot conclude for example that Microsoft spent $1 million lobbying on immigration. Instead, we can state that Microsoft spent $1 million lobbying and listed immigration as a lobbying issue, along with other issues like taxation and the environment.

Independent Variable

For my independent variable I take firms' annual capital expenditures, the latter being an indicator used previously as proxy to capture firms' technology, and by extension automation inputs (Barth et al. 2022; Varkiani and Chelaru 2020; Zolas et al. 2020). Capital expenditures represent the funds used by a company in order to acquire, upgrade, and maintain physical assets such as property, plants, buildings, technology, or equipment (Fernand, James, and Kvilhuag 2022). Admittedly, this metric is far from perfect since capital expenditures constitutes the sum of firm spending in the acquisition of material objects (from physical buildings to equipment). Thus, capital expenditures may be too broad as a metric and not provide the same type of precision in measuring firm reliance on business technology as we saw with ABS measures that asked firms to outline how much of their production needs were met by robotics, or machine learning, for example.

Nevertheless, firm-capital expenditures do capture firm-level spending on the procurement and maintenance of material objects and entities (i.e., non-labor) that they deem necessary for the purpose of producing goods/services expenditure that include numerous technologies to meet their production needs, which in turn can complement or displace labor. Therefore, although imperfect, capital expenditures capture several aspects of firm-level purchase and expenditure that include numerous technologies to meet their production needs, which in turn can complement or displace labor.

Table 8-1: Summary Statistics

Variable	Variable Description	Mean	SD	Min.	Max.
Immigration_Lobby_Issue_Amount: Immigration Expenditures	Firm Immigration Lobbying Expenditures ($ Thousands) (Based on the annual number of lobbying reports listing immigration as lobbying issue): Source (CRP)	30.30	211.86	0	4,620.0
Total.Immigration.Lob: Immigration Reports	Number of Reports Listing Immigration as Lobbying Issue: Source (CRP)	0.5	3.0	0	64.0
Amount: Lobbying Expenditures	Total Lobbying Expenditures ($ Millions): Source (CRP)	7.81	28.40	0	565.0
Total.Issues.Lobbied: Lobbying Reports	Total Number of Lobbying	39.3	83.59	0	823

	Reports: Source (CRP)				
Capital.Expenditures: [75] Capital Expenditure	Annual Firm Capital Expenditures ($ Millions): Source (Eikon)	734.06	2,313.63	0	37,958.0
Trade.Union.Representation: Total Union Representation	Percentage of employees represented by independent trade union organizations or covered by collective bargaining agreements: Source (Eikon)	6.7	16.18	0	100
Annual.Number.of.Certified.LCA.Visas: Labor Condition Application	Total Number of Certified LCA Applications for non-immigrant visas for foreign workers (H-1B, H-1B1, and E-3): Source (DOL)	47	349	0	11,763.0

Note. Number of observations = 3653. SD = Standard Deviation, Min. = minimum, Max. = Maximum, CRP = Center for Responsive Politics, DOL = Department of Labor

[75] Total sum of (million $): Purchase of Fixed Assets, Purchase Acquisition of Intangibles, and Software Development Costs: Source (Eikon)

Data on firms' capital expenditures were taken from Refiniv Eikon, where I was able to obtain information on Public Companies incorporated in the United States, traded on the New York Stock Exchange and/or the National Association of Securities Dealers Automated Quotations Sock Market (NASDAQ). Specifically, I looked at firms' cumulative capital expenditures, which, "Represents the sum of: Purchase of Fixed Assets[76], Purchase Acquisition of Intangibles[77], and Software Development[78] Costs" (Refinitiv Eikon). In particular, I was able to obtain information on firms' capital expenditures from these publicly traded companies between 2008 to 2021 (fiscal year).

Controls

Questions and concerns, about the motives behind firms' immigration lobbying have been raised by critics who see firm reliance on immigrant labor as merely a ploy to procure a productive, yet exploitable and submissive workforce (Shah 2021; Wishnie 2007). Foreign workers are generally more complacent to the demands of employers, out of fear that by failing to comply with their employers' demands, this in turn may jeopardize their status and stay in the United States (Shah 2021).

To control and gauge the extent to which firms are driven by more exploitative reasons to lobby for immigration, I include a variable listing firm-level union representation,

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[76] Fixed assets (FA), refers to tangible assets or property, plant and equipment. As a term, FA often describes assets and property that cannot be easily converted into cash. Specifically, Eikon references Fixed Assets describe: "Net Property, Plant & Equipment, Net Intangibles, Long Term Investments, Other total Long-Term Assets" (Refinitiv Eikon).

[77] Intangibles, "Consists of patents, copyrights, franchises, goodwill, trademarks, trade names, secret processes, and organization costs. Intangibles, Gross represents the gross amount of intangibles before being reduced by Accumulated Intangible Amortization" (Refinitiv Eikon).

[78] Software Development refers to the process of conceiving, specifying, designing, programming, documenting, testing, and bug fixing involved in creating and maintaining applications, frameworks, or other software components. Software development involves writing and maintaining the source code, but in a broader sense, it includes all processes from the conception of the desired software through to the final manifestation of the software, typically in a planned and structured process (for more information please see: https://www.bestpricecomputers.co.uk/glossary/application-development.htm.).

which summarizes the annual percentage of employees represented by independent trade union organizations or covered by collective bargaining agreements (Refinitiv Eikon). The rationale for utilizing this variable is twofold. First, the more of a firm's employees are represented by a union, the more likely the firm in question could be pressured through the collective bargaining agreement, to allow incoming employees, including foreign born workers, to join the union (Costa 2021; Employer/Union Rights and Obligations | National Labor Relations Board n.d.). Second, there may be pushback against a firm from unionized employees, if the firm in question were caught recruiting foreign born workers with the intent of paying them less than their domestic counterparts (O'Brien 2022; Ramirez 2022). Thus, if immigration lobbying were driven by firms' desire to exploit a complacent labor force, then we would expect to see less lobbying activity among firms that have a higher number of unionized workers.

Additionally, as authors like Peters (2017) contend, firms have shifted their support from low-skilled immigration in favor of high-skilled immigration to meet their capital-intensive production needs. Currently, federal law has capped the number of LCA visas that can be issued to companies in general (at 65,000 visas, with an additional 20,000 slots allocated for workers with graduate degrees from universities in the United States) (Dixon-Luinenburg 2022). Given that some of the largest firms benefit from reliance on LCA type of immigrations, and the fact that lobbying is a costly and difficult activity that is usually incurred by larger firms that *already* find themselves lobbying and have vested interests in existing policies[79] (Baumgartner et al. 2009; Drutman 2017; Kerr, Lincoln, and Mishra 2014), we should see a positive correlation in which the higher the annual number of

[79] See Chapter 3 for more information.

certified LCA applications a firm obtains, the more likely they would incur in higher lobbying expenses on immigration.[80]

8.2 Empirical Tests and Results

Table 8-1 lists the variables, including their respective summary statistics, used for the analysis. Consistent with literature that analyzes lobbying expenditures as an outcome variable, I log transform firms' lobbying expenditures to mitigate the influence of outliers in the estimation of coefficients (Delmas, Lim, and Nairn-Birch 2016; Goldstein and You 2017; Hansen and Mitchell 2000; Kerr, Lincoln, and Mishra 2014; Kim 2017; Richter, Samphantharak, and Timmons 2009; Ridge, Ingram, and Hill 2017). Thus, most of the estimation models discussed in this section, entail the log transformation of variables like firms' immigration lobbying expenditures, firms' capital expenditures, and firms' certified LCA visa applications, as a way to deal with the broad and skewed distributions and outliers of these variables.

Equation 1 summarizes the first empirical model I tested where log_imm_lob_amount, represents the natural logarithm of firms' cumulative immigration lobbying expenditures, while log_cap_exp, represents the natural logarithm of firms' annual capital expenditures, to create a basic bi-variate pooled OLS model. Thus, we begin by looking initially at a bi-variate relationship involving firms' capital expenditures as independent variable (IV) and firms' immigration lobbying expenditures as dependent variable (DV). Column 1 of Table 8-2[81] summarizes this initial bi-variate relationship between the two variables of interest using OLS. Given that we are using natucorrespondhms

[80] Since 2004, when the LCA cap was "re-introduced" many of the top firms that employ LCA visa workers have come out pushing for policy that would both facilitate and permit them to increase reliance on LCA workers (McGill 2022).

[81] Given the prospect of heteroskedasticity and autocorrelation in our sampled panel, I use clustered standard errors, instead of robust standard errors.

at both the IV and DV level, we can interpret that column 1 is telling us that a 1% increase in firms' capital expenditures corresponds to approximately a 0.10% increase in immigration lobbying expenditures. The results of this initial bivariate model are statistically significant.

Equation 1: Basic Bi-variate OLS Model

$$\text{log\_imm\_lob\_amount} = \beta_0 + \beta_1 \text{log\_cap\_exp} + \varepsilon$$

Equation 2: Basic Multivariate OLS Model

$$\text{log\_imm\_lob\_amount} = \beta_0 + \beta_1 \text{log\_cap\_exp} + \beta_2 \text{Trade.Union.Representation} + \beta_3 \text{log\_lca} + \varepsilon$$

In equation 2, I include the control variables discussed in the previous section. I introduce the $\text{Trade.Union.Representation}$ variable to control for firms' trade union representation, as well as log_lca, the natural logarithm of firms' annual LCA visa certifications, to assess whether immigration lobbying is primarily driven by firms' desire to procure foreign-born, high-skilled workers. Once I introduce these controls to the pooled OLS model, we see some change as summarized in Column 2 of Table 8-2. Now we see that for every 1% increase in firms' capital expenditures, there is a corresponding 0.6% increase in firms' lobbying expenditures, while holding other variables constant, which is still at statistically significant levels ($p<0.01$). When we look at the variable Trade.Union.Representation, we see that for every unit increase in firms' union representation there is a corresponding 0.01 percent decline in lobbying expenditures. These findings are not statistically significant and are substantively close to 0. Lastly, we see that when controlling for the number of certified LCA visas, we notice that for every 1 percent increase in the LCA certified visa applications, we can observe an increase of about 0.33% immigration lobbying expenditures also at statistically significant levels.

Fixed Effects

Given that we are dealing with longitudinal data, we have to consider the prospect of unobserved heterogeneity (i.e., an unmeasured or unobserved variable). For example, time-period 2008-2021, is one that has witnessed recessions (2008-2009), a pandemic (2020-2021), and a series of other significant factors that have likely influenced firms' decisions on issues like capital expenditures and immigration lobbying. Additionally, there may be firm characteristics, e.g., their size, age, formalized structure, research and development (R&D), that also affect firms' decisions on matters like lobbying and/or capital expenditures. Summarizing, there may be a series of omitted variables that could both explain changes in firms' annual capital expenditures, as well as their immigration lobbying expenditures. If not properly accounted for, or modeled, these heterogeneities may in turn produce endogeneity bias, thereby undermining the model in question (Wooldridge 2013, 460).

One way to control these types of unit-level and time-level confounders is using unit-level and time-based fixed effects (Imai and Kim 2019; Mummolo and Peterson 2018). In our case, this would mean controlling for $FirmNo_i$, i.e., the unobserved time-invariant individual firm-level fixed effect, as well as $Year_t$, which captures time-specific trends (e.g., recession).

Equation 3 summarizes the first fixed effects model, where $log\_imm\_lob\_amount_{\mathrm{i,t}}$, represents the natural logarithm of firm *i*'s immigration lobbying expenditures in year *t*, as an outcome of $log\_cap\_exp_{\mathrm{i,t}}$ the natural logarithm of firms' annual capital expenditures, $Union_{i,t}$, controlling for firms' trade union representation, and $log\_lca_{\mathrm{i,t}}$ which takes the natural logarithm of annual certifications of firms' LCA visa applications. Lastly, to control for unobserved unit-lever heterogeneity, I include firm fixed effects $\mathrm{FirmNo_i}$, and $\mathrm{YearNo_t}$ to capture any time-specific trends (e.g., recession).

Equation 3

$$\text{log\_imm\_lob\_amount}_{i,t} = \alpha_1 \text{log\_cap\_exp}_{i,t} + \alpha_2 \text{Trade.Union.Representation}_{i,t} + \alpha_3 \text{log\_lca}_{i,t} + \varphi \text{FirmNo}_i + \delta \text{YearNo}_t + \varepsilon_{i,t}$$

Column 3 of Table 8-2 summarizes the results when we introduce only firm fixed effects to our panel model. Now we note that for every one percent increase in capital expenditures by firm, per year, there is a 0.062 percent increase in firm-immigration lobbying by year, with results no longer being statistically significant. In fact, results are not statistically significant for any of the control variables either. Results change however, when we include fixed effects for time. In this case, all results are significant.

Table 8-2: OLS and Fixed Effects

	log_imm_lob_amount				
	OLS		panel linear		
	Basic Bi-Variate	Multi-variate	De-Meaned	De-Meaned	Two Ways
	(1)	(2)	(3)	(4)	(5)
log_cap_exp	0.095***	0.062***	0.026	0.060***	0.011
	(0.008)	(0.008)	(0.016)	(0.015)	(0.017)
Trade.Union.Representation		0.010***	0.006	0.011***	0.006
		(0.004)	(0.005)	(0.003)	(0.005)
log_lca		0.329***	0.087	0.334***	0.081
		(0.046)	(0.058)	(0.043)	(0.057)
Constant	-0.699***	-0.682***			
	(0.115)	(0.114)			
Fixed effects?	No	No	Firm	Year	Firm and Year
N	3,653	3,653	3,653	3,653	3,653
R^2	0.027	0.058	0.004	0.057	0.002
Adjusted R^2	0.027	0.057	-0.080	0.053	-0.086
Residual Std. Error	3.143 (df = 3651)	3.094 (df = 3649)			
F Statistic	101.899*** (df = 1; 3651)	74.574*** (df = 3; 3649)	4.450*** (df = 3; 3369)	73.040*** (df = 3; 3637)	2.214* (df = 3; 3357)

*p < .1; **p < .05; ***p < .01

Fixed effects estimated but not shown in Fixed Effects column. Cluster-robust standard errors are used.

In the context of the literature, the convention is to lag the explanatory variable because of the danger of simultaneity bias; i.e. a situation in which the explanatory variable is jointly determined with the dependent variable. To control for simultaneity, and endogeneity more broadly, much of the literature lags all explanatory variables by at least one time period (Delmas, Lim, and Nairn-Birch 2016; Facchini, Mayda, and Mishra 2011; Hill et al. 2013; Kerr, Lincoln, and Mishra 2014; Richter et al. 2009; Ridge, Ingram, and Hill 2017). In our case, just like it is conceivable that capital expenditures affect firms' immigration lobbying expenditures, it is also possible that firms' changes in firms' lobbying expenditures affect firms' capital expenditures.

Equation 4: Lagged Independent Variables

$$\begin{aligned}\mathrm{log\_imm\_lob\_amount}_{i,t} &= \mathrm{log\_cap\_exp}_{i,t-1} + \gamma_2 \mathrm{Trade.Union.Representation}_{i,t-1} + \gamma_3 \mathrm{log\_lca}_{i,t-1} \\ &+ \varphi \mathrm{FirmNo}_i + \delta \mathrm{Year}_t + \varepsilon_{i,t}\end{aligned}$$

Equation 4 features an estimation model in which the three explanatory variables are lagged by one time period. Once we lag all explanatory variables, we notice that firms' annual capital expenditures has a statistically significant effect on firm lobbying, when looking at firm and year fixed effects but not when controlling for both firm and time fixed effects. We see that when looking at firm only and year only fixed effects, columns 1 and 2 of Table 8-3, respectively, results are statistically significant for the relationship between the lagged explanatory variable log_cap_exp_1 and log_imm_lob_amount.

In addition, in looking at Table 8-4, a correlation matrix involving the main variables in our analysis in Table 8-2 and Table 8-3, we can see that there is no collinearity between our explanatory variables. Generally, the convention dictates that instances in which the correlation between variables is greater than 0.9 or lower than -0.9, is indicative of collinearity. Thus, we can conclude from looking at Table 8-4 that multicollinearity between our explanatory variables is not the culprit for why our estimates lose their significance. One important thing from Table 8-4 is that there is a large positive correlation between capital expenditures and immigration lobbying expenditures, which may explain why at the level of a basic OLS bi-variate model in Table 8-2 there is a statistically significant relationship involving those two variables.

Table 8-3: Fixed Effects Lagged by One-time Period.

	log_imm_lob_amount		
	De-Meaned	De-Meaned	Two Ways
	(1)	(2)	(3)
log_cap_exp_1	0.029**	0.064***	0.024
	(0.014)	(0.013)	(0.015)
Trade.Union.Representation_1	-0.001	0.009***	0.001
	(0.004)	(0.002)	(0.004)
log_lca_1	0.107**	0.342***	0.117**
	(0.054)	(0.050)	(0.054)
Fixed effects?	Firm	Year	Firm and Year
N	3,653	3,653	3,653
R^2	0.006	0.059	0.005
Adjusted R^2	-0.077	0.055	-0.082
F Statistic	6.826*** (df = 3; 3369)	75.553*** (df = 3; 3637)	5.978*** (df = 3; 3357)

*p < .1; **p < .05; ***p < .01

Fixed effects estimated but not shown in Fixed Effects column. Cluster-robust standard errors are used.

Interestingly, column 3 of Table 8-3 reveals that there continues to be a statistically significant relationship between the firms certified LCA Visa applications (lagged by one time period) and their immigration lobbying expenditures. However, it is also worth noting that usually the firms that lobby individually on immigration, tend to be larger and more solvent firms from sectors like Manufacturing and Information (e.g., Microsoft, Amazon.com, and Alphabet), which in turn are more likely to recruit high-skilled workers to meet their production needs in the first place. By contrast, firms that rely on low-skilled immigrations, including low-skilled immigrant workers (e.g., H-2A and H-2B visas) tend to lobby collectively as part of trade associations. Because our data looks only at the lobbying activity of individual firms, and because the top firms that lobby individually on immigration are firms that rely primarily on LCA type foreign workers, this in turn may explain why we continue to see a statistically significant relationship between firms' certified LCA visa applications and their immigration lobbying expenditures. If we were also able to observe firm lobbying expenditures from firms that rely on non-LCA visas, then these statistics could be different.

Table 8-4: Correlation Matrix

	Immigration_Lobby_Issue_Amount	Capital.Expenditures	Trade.Union.Representation	Annual.Number.of.Certified.LCA.Visas
Immigration_Lobby_Issue_Amount	1.00	0.29	0.02	0.22
Capital.Expenditures	0.29	1.00	0.13	0.33
Trade.Union.Representation	0.02	0.13	1.00	-0.01
Annual.Number.of.Certified.LCA.Visas	0.22	0.33	-0.01	1.00

In addition, the F-Statistics at the bottom of all models in Table 8-2 and Table 8-3 are all statistically significant. Suggesting at the very least that the inclusion of the coefficient for each model in question are significant when used jointly to explain the outcome of interest, in this case immigration lobbying; i.e., when looking at the model as a whole, in particular the model summarized under column 5 of Table 8-2 and Column 3 of Table 8-3, we can reject the null hypothesis that the coefficients in question are equal to 0.

8.3 Additional Tests

Two important issues arise amid any analysis that looks at lobbying as an outcome (i.e., analysis in which lobbying is the dependent variable). The first challenge revolves around the issue of censored data, a situation in which the value of measurements or observations is partially known (Bombardini 2008; Goldstein and You 2017; Hansen and Mitchell 2000; Hill et. al 2013; Kim 2017; Ridge, Ingram, and Hill 2017).

In the case of lobbying, per the Lobbying Disclosure Act (LDA), we know that lobbying clients (in our case firms) are not required to disclose lobbying contributions equal to, or less than $10,000.[82] When we look at our sampled data, we can observe that the lowest contribution recorded was equal to $10,000. In our sampled data, in situations in which firms' lobbying expenditures are recorded as $0, we are not sure whether this is because the firm did not lobby at all (i.e., it's contributions were equal to 0), or if the lobbying contributions equal to, or below, $10,000 and therefore not recorded appearing as if the firm *did not* lobby at all.

Censored data produces a problem akin to that of missing data, i.e., there can be threats of misspecified statistical models, bias in the estimates of parameters, or a reduction in the overall representativeness of the sample (Kang 2013). One way through which scholars deal with the prospect of censored data, particularly in the context of measuring lobbying, is

[82] Per current lobbying filing rules, a lobbying firm (i.e., a firm hired by someone to lobby for them) does not have file a report who do not spend at least $ 3,000 during a quarter. Likewise, in situations in which actors rely on in-house lobbyists (i.e., lobbyists that work directly for the actor in question) are not required to state lobbying expenditures of an actor who spends less than $12,500 in a given quarter. For more information, please see: https://www.opensecrets.org/federal-lobbying/methodology.

through estimating a tobit model (sometimes also called the censored regression model). A tobit model estimates the linear relationship between variables when there is right-[83] or left-censoring[84] of the dependent variable. Indeed, in our case we note that there was a total of 3,375 observations, where sampled firms' immigration lobbying expenditures were equal to 0. Thus, we can ask ourselves whether situations in which lobbying contributions are equal to 0 occur because a firm simply did not lobby, or whether their lobbying contributions fell below the threshold (i.e., less than $10,000) and thus were not recorded.

Equation 5:

$$\text{log\_imm\_lob\_ammount} = \xi_1 \text{log\_cap\_exp} + \xi_2 \text{Trade.Union.Representation} + \xi_3 \text{log\_lca} + \omega$$

$$\begin{array}{ll} \text{Y} = \text{log\_imm\_lob\_ammount} = \xi_1 \text{log\_cap\_exp} + \ldots + \omega & \text{if } 0 < \text{RHS}^{85} \leq 10{,}000 \\ \text{Y} = 0 & \text{Otherwise} \end{array}$$

Column 1 of table 8-5 summarizes the results of a basic pooled OLS model as depicted by the first row of equation 5. Equation 5 proposes the following, are situations in which lobbying contributions are equal to 0, representative of an interaction of our independent variables yielding a value of 0 for our dependent variable or would interaction of our independent variables have yielded value for lobbying contributions higher than 0, had measurements of lobbying expenditures not been censored.

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[83] Right-censoring, sometimes also referred to as censoring from above, occurs when values above a threshold, are given the value of that threshold. E.g., if a stadiometer (the piece of medical equipment used to measure human height) measures height only up until 2 meters (about 6 ft and 6 in) then all individuals' who are over 2 meters tall, will not have their heights properly recorded, or have their height recorded as 2 meters tall, when they could in fact be taller. For more information please see: https://stats.oarc.ucla.edu/r/dae/tobit-models/.

[84] Left-censoring, sometimes referred to as censoring from below, is like right-censoring, albeit with data being censored once it falls below a certain threshold. In the case of lobbying, per the LDA, lobbying contributions that are below $10,000 are not recorded.

[85] Refers to the Right-Hand Side of the equation

In looking at Table 8-6, we see that a difference in 1 log of Firm Capital Expenditures, on average, increases the probability of a 1 log change in firm Immigration Lobbying by 3 percent. Thus, it appears that changes in capital expenditures by firms are conducive to a very small change in the likelihood that firms will incur additional lobbying expenditures on immigration, even if results are statistically significant.

Table 8-5: Tobit Model for Immigration Lobbying Expenditure

	Dependent variable:	
	log_imm_lob_amount	
	OLS	*censored regression*
	(1)	(2)
log_cap_exp	0.062***	0.585***
	(0.010)	(0.075)
Trade.Union.Representation	0.010***	0.019**
	(0.003)	(0.009)
log_lca	0.329***	0.614***
	(0.031)	(0.088)
logSigma		1.667***
		(0.053)
Constant	-0.682***	-10.647***
	(0.166)	(1.632)
Observations	3,653	3,653
R^2	0.058	
Adjusted R^2	0.057	
Log Likelihood		-1,423.244
Akaike Inf. Crit.		2,856.488
Bayesian Inf. Crit.		2,887.505
Residual Std. Error	3.094 (df = 3649)	
F Statistic	74.574*** (df = 3; 3649)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Moreover, due to computational issues, it is not possible to estimate a fixed effects tobit model in R. [86] Nor is it possible to estimate marginal effects of panel data[87] in R. This means that Table 8-5 represents findings using Pooled OLS, which, as we have discussed, likely contains unobserved heterogeneity.

Table 8-6: Marginal Effects

	Marg. Eff.	Std. Error	t value	Pr(>|t|)
log_cap_exp	0.03	0.00	10.04	0.00
Trade.Union.Representation	0.00	0.00	1.99	0.05
log_lca	0.03	0.00	6.18	0.00

The second challenge that arises with lobbying data is the prospect of selection bias, specifically self-selectivity (Bombardini 2008; Delmas, Lim, and Nairn-Birch 2016; Hansen and Mitchell 2000; Hill et al. 2013; Kerr, Lincoln, and Mishra 2014; Richter et al. 2009; Ridge, Ingram, and Hill 2017). Selection bias is often caused by the reliance on data that was produced by the non-random sampling of a target population. Non-random sampled data is more likely to feature certain units from a target population over others, thus risking the possibility that the sample obtained is not truly representative of the population as a whole (Gujarati and Porter 2009). In the context of the CRP, we know that we can only observe information on lobbying, including expenditures from firms that lobbied. As we have discussed in chapter 3, lobbying is costly and laborious, and it is more likely for more solvent firms to lobby in general and individually (i.e., not as part of a trade association). In other words, there may be unobserved and/or unmeasured factors that explain firms' decision to

[86] For more information see https://cran.r-project.org/web/packages/censReg/vignettes/censReg.pdf.
[87] For more information see https://cran.r-project.org/web/packages/censReg/censReg.pdf.

lobby in the first place (Delmas, Lim, and Nairn-Birch 206; Kerr, Lincoln, and Mishra 2014; Kone et al. 2019).

Equation 6:

$$P(\mathrm{lobbied}_{i,t} = 1 \mid Z) = \Phi(Z)$$
$$= \Phi(\zeta_1 \mathrm{log\_cap\_exp}_{i,t-1} + \zeta_2 \mathit{Trade}.\mathrm{Unio.Representation}_{i,t-1} + \zeta_3 \mathrm{log\_lca}_{i,t-1} + \zeta_4 \mathrm{lobbied}_{i,t-1} + \mu_{it})$$

Equation 7

$$\mathrm{log\_imm\_lob\_amount}_{it} = \theta_1 \mathit{log\_cap\_exp}_{i,t-1} + \theta_2 \mathrm{Trade.Union.Representation}_{i,t-1} + \theta_3 \mathrm{log\_lca}_{i,t-1} + \varphi \mathrm{FirmNo}_i + \delta \mathrm{Year}_t + \eta\lambda + \upsilon_{i,t}$$

One estimation approach that is often used within the literature to deal with the prospect of selection bias is the Heckman selection model[88] (Brasher and Lowery 2006; Delmas, Lim, and Nairn-Birch 2016; Hansen and Mitchell 2000; Hill et al. 2013; Kerr, Lincoln, and Mishra 2014; Richter et al. 2009). In practice, the Heckman selection model consists of a two-step approach to correct for non-randomly selected samples. The first step, (also referred to as the first stage or selection stage), as seen in equation 6, entails using a probit model to estimate the propensity to lobby, where the dependent variable, in our case **lobbied**, is a dichotomous variable (1,0) that expresses whether a firm in question lobbied (regardless of issue, or not).

Being a probit model, in equation 6 Φ (·) represents the cumulative distribution function.[89] The results of this first stage probit can be found on column 2 of Table 8-8. We

[88] The Heckman selection model (sometimes referred to as the Heckman Selection Strategy or the Heckman Correction) is a statistical technique used to correct bias from non-randomly selected samples. In practice, the Heckman selection relies on existing observational data and begins by assessing what is the likelihood of having a unit of observation being observed in the first place. Thereafter, the model establishes that we must consider the likelihood of having a unit being observed in the first place, when factoring the outcome of interest (Heckman 1976).

[89] For more information please see: https://www.econometrics-with-r.org/11-2-palr.html.

notice that log capital expenditures and log certified LCA applications are good predictors of the likelihood of log immigration lobbying, at statistically significant levels.

Table 8-8: Heckman Selection Model

	Dependent variable:		
	log_imm_lob_amount	lobbied	
	OLS	*Heckman selection*	
	FE	selection	outcome
	(1)	(2)	(3)
log_cap_exp_1	0.024**	0.019***	0.095***
	(0.011)	(0.005)	(0.019)
Trade.Union.Representation_1	0.001	0.001	0.004
	(0.004)	(0.002)	(0.005)
log_lca_1	0.117***	0.033*	0.400***
	(0.037)	(0.017)	(0.045)
lobbied_1		2.255***	
		(0.056)	
Constant	4.022***	-1.357***	-0.759**
	(0.649)	(0.091)	(0.358)
Fixed effects?	Yes	No	Yes
Observations	3,653	3,653	3,653
R^2	0.586	0.062	0.062
Adjusted R^2	0.549	0.060	0.060
rho		-0.127	-0.127
Inverse Mills Ratio		-0.490** (0.210)	-0.490** (0.210)
Residual Std. Error	2.139 (df = 3357)		
F Statistic	16.080*** (df = 295; 3357)		
Note:			*p<0.1; **p<0.05; ***p<0.01
			Fixed effects estimated but not shown in Fixed Effects column

The first step of the Heckman model also produces the estimation of the propensity or "hazard rate," or inverse Mill's ratio[90] (IMR) (Delmas, Lim, and Nairn-Birch 2016; Hill et al. 2013; Kerr, Lincoln, and Mishra 2014; Richter et al. 2009). This IMR (λ) is included in the

[90] The inverse Mills ratio is the ratio of the probability density function (a function used to specify the probability that a random variable will fall within a particular range of variables) to the complementary cumulative distribution function (a function expressing the probability that a random variable will be greater than, or less than a particular level) (Wooldridge 2009).

second step, as seen in equation 7, and summarized in column 2 and 3 of Table 8-8. We note from equation 7 that the IMR also has a coefficient, like the other covariates, in this case η. Generally, when the coefficient of the IMR is not statistically significant, in principle, this is suggestive that there is no selection bias. In our case though, the coefficient η is statistically significant, which suggests that there is a correlation between μ from equation 6, and υ from equation 7, thereby warranting that we rely on the Heckman model to correct for selection bias.

Nevertheless, we see that even with the Heckman selection model, the coefficients in column 3 are not significantly different from those in column 1 of Table 8-8. Log capital expenditure is statistically significant as seen in column 1 and column 3 of Table 8-8. However, given that firms that lobby individually, usually lobby for multiple political issues at once, it may be that what we really have is a relationship between capital expenditures and lobbying and not necessarily one that is as clear when we look at capital expenditures and immigration lobbying.

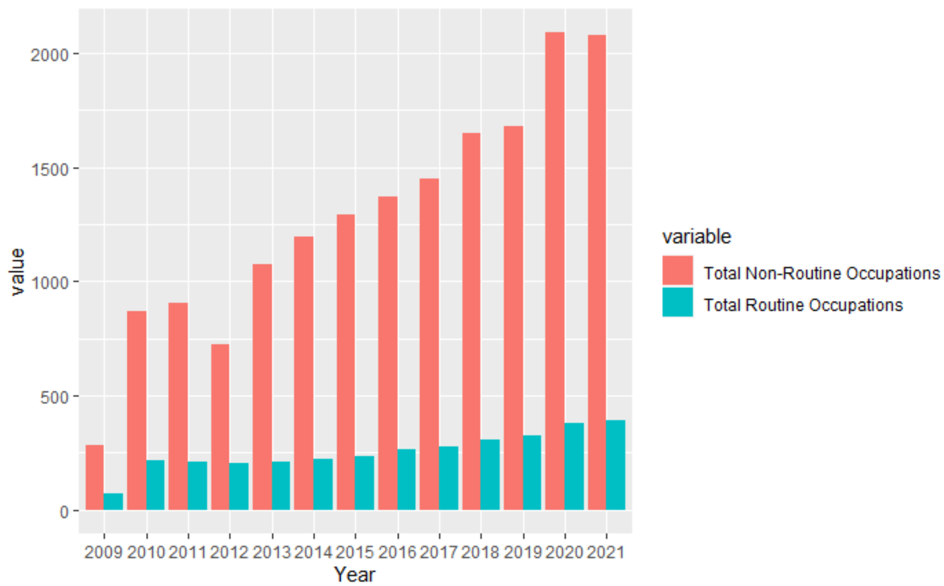
CHAPTER 9. INSTRUMENTAL VARIABLE

As discussed in Chapter 4, the task-based models predict that the effects of automation and new technologies in general on labor are mediated through the tasks performed by labor. Ideally, we would want to see how firm-reliance on automation (measured through the firm adoption and use of different technologies to meet their production needs) alters the labor composition of those same firms, and by extension demand for immigrant labor (operationalized as firm-immigration lobbying). Instead, we must take a multi-step approach where we look first whether new technologies' effect on routine and non-routine occupations and thereafter whether the increase of changes in labor composition along routine/non-routine lines can explain firm-immigration lobbying. In Figure 9-1, we see how between 2009 and 2021, more non-routine occupations have been issued H1 type visas, when compared to the number of those same types of visas issued to routine occupations.

However, two issues arise even if we are to take this multi-step approach. The first, as discussed in chapters 7 and 8, is the absence of clear and accurate measurements for firm-level use of automation. One way to deal with this, as discussed in chapter 8, is to use the measurement of firm-capital expenditures, a measure that while imperfect, given how broad it is in accounting firms' assets, does at least include all firm-level spending on things like machines and software to meet their production needs. The second problem is the possibility of an endogenous relationship between visas and lobbying.

For example, is it the case that greater reliance on non-routine labor (measured in number of H1 type visas issued to non-routine occupations) increases firm-immigration lobbying? Or is it the case that more immigration lobbying leads to more H1-type visas being issued to non-routine occupations? Furthermore, the possibility of an omitted variable remains, in the sense that it may be that an unspecified variable is affecting why firms are obtaining more non-routine H1 type employees, and also, why they are lobbying more for immigration.

Figure 9-1: Routine and Non-Routine H1 Type Visas by year



Source: Department of Labor's Labor Certification data.

To address the possibility of endogeneity, while ensuring that we keep up with our multi-step approach of analysis, I rely on an instrumental variable approach. In short, I use firm-level capital expenditures as an instrument, with the number of certified H1 type visas issued to non-routine occupations, by firm, by year as the independent variable, and thereafter the number of times firms list immigration as lobbying issue, in a given year, as the dependent variable. Figure 9-2 summarizes the logic of the instrumental variable approach. The approach is imperfect, but the best option given available data.

As discussed in the Additional Tests Chapter, I log transform firm-level capital expenditures to mitigate the influence of outliers in the estimation of coefficients. Thus, the instrument consists of the natural logarithm (ln) of the sampled firms' annual capital expenditures (ln(Cap.exp+1)), for every firm *i.* In the context of the literature, we find instances in which non-binary and/or continuous variables are used as instruments (e.g., Acemoglu, Johnson, and Robinson 2001; Jensen and Rosas 2007; Pierskalla and Hollenbach 2013), warranting the inclusion of log capital expenditures as instrument.

Figure 9-2: Instrumental Variable

Firm-Level Capital Spending Instrument	➔	Non-Routine H1 Visas Independent Variable	➔	Immigration Lobbying Reports Dependent Variable

We can summarize the logic of figure 9-2 as suggesting, first, a positive correlation between firms' capital expenditures and the number of non-routine foreign workers (measured by the number of certified LCA visas issued to a given firm for non-routine workers). In short, for every percentage point increase in firms' capital expenditures, we should expect a positive percentage point increase in the number of certified non-routine foreign workers per firm. Thereafter, per the logic of figure 9-2, we should also expect to see that the more companies rely on non-routine foreign-born workers, the more likely they are to list immigration as a lobbying issue.

One potential objection to this approach may be that capital expenditures is itself correlated with immigration lobbying. In the context of instrumental variables, one of the main assumptions is that the instrument is not correlated with the dependent variable, save through the independent (endogenous variable). In short, if the instrument is correlated with the dependent variable, we are in essence violating the exclusion restriction assumption. Ergo, it could be that firm capital expenditure is correlated with firm lobbying. For example, firm capital expenditures may influence questions of firm political lobbying, or questions of firm lobbying may influence decisions about capital expenditures.

However, we must note that what is under discussion here is not whether firm capital expenditure is an instrument for firm lobbying in general, nor whether capital expenditures is an instrument for how much money a firm spends lobbying. Instead, I am proposing that we look at firm-level capital expenditure as an instrument for whether firms list immigration as a lobbying issue in their lobbying reports, as part of their lobbying activity. Given how ubiquitous firm lobbying has become, especially for larger firms, my assumption is that capital expenditure be considered not as predictor of lobbying but rather as an indirect influence on whether firms list immigration lobbying as a political issue.

Another consideration, when using an instrumental variable, is the Stable Unit Treatment Value Assumption (SUTVA). Formally, SUTVA posits that the potential outcome of a given unit, in our case firm immigration lobbying, should not be influenced by the relationship between the instrument—via the independent variable—on the dependent variable. Given that the panel data I use consists of firms from different economic sectors, I argue that it seems highly unlikely that the capital expenditures of a given firm will influence the immigration lobbying of firms in a completely different economic sector. E.g., it is highly unlikely that Coca-Cola Co.'s annual capital expenditures influence the number of times Hasbro Inc. (a toymaker) lists immigration as a lobbying issue.

However, there may be exceptions. For example, capital expenditures by a company like Microsoft may enable it to produce software that is then purchased as capital by other firms like Coca Cola or Hasbro to meet their production needs, thereby influencing their immigration lobbying. While this is in part conceivable, I propose that given that firms' capital expenditures consist of more than just buying software from one source, and often entails reliance on different sources for machinery and physical assets (e.g., although

Microsoft's capital expenditure could have an indirect effect on other firms) this alone would be insufficient to significantly affect the number of times that Coca Cola listed immigration as a lobbying issue.

For this analysis I once again rely on data from the Center for Responsive Politics (CRP) for information on firm lobbying reports, Refinitiv Eikon for information on firms' annual levels of capital expenditures, and the Department of Labor's (DOL) Performance Data for information on the number of LCA (labor condition applications, i.e., H1-type visas). In addition, I rely on information from the DOL's Performance data, along with O*NET to obtain the Routine Task Index for occupations that were issued certified H1-type visas (for more information, see chapter 6). In short, building on these sources I constructed a panel dataset consisting of 281 distinct firms, with observations between 2009 and 2021 (i.e., 13 years).

Equation 1: 2SLS With Time and Unit Fixed Effects
First Stage:

$$\begin{aligned}\mathrm{Non.Routine}_{i,y-1} &= \pi_0 + \pi_1 \mathrm{log\_cap\_exp}_{i,y-1} + \pi_2 \mathrm{lobbied}_{i,y-1} + \pi_3 \mathrm{Trade.Union.Rep}_{i,y-1} \\ &\quad + \varphi_i + \tau_y + \nu_{i,y-1}\end{aligned}$$

Second Stage

$$\begin{aligned}\mathrm{Tot.Immigration.Lob}_{\,i,y} &= \lambda_0 + \lambda_1 \mathrm{Non\_}\widehat{\mathrm{Routine}}_{i,y-1} \quad \lambda_2 \mathrm{lobbied}_{i,y-1} + \lambda_3 \mathrm{Trade.Union.Rep}_{i,y-1} \\ &\quad + \varphi_i + \tau_y + \mu_{i,y-1}\end{aligned}$$

Equation 1 formally summarizes the two-stage least squares (Instrumental Variable, IV-2SLS) equation model. The first stage summarizes the relationship between the instrument, capital expenditures, and the independent variable, number of certified LCA visas for non-routine occupations, by firm, per year), whereby we look at log capital expenditures by firm *i*. The endogenous regressor (independent variable) is the number of certified LCA visas issued to non-routine occupations, per sampled firms. In addition, I include as control variables, whether the firm in question lobbied (irrespective of political issue) in a given year as a dummy variable, as well as information on trade union representation, by firm (for more information see Chapter 8).

Furthermore, I include firm-level fixed effects (φ_i) and time fixed effects (τ_y) to control for unobserved unit and time-level heterogeneities. The second stage is nearly identical to the first stage, albeit now looking at the relationship between number of certified LCA visas issued to non-routine occupations, per sampled firms, as the explanatory variable, and the number of reports listing immigration as a lobbying issue, per firm *i*. In equation 1 we see how the instrument, controls, and endogenous explanatory variable are all lagged by one time period, to control for the possibility of simultaneity or endogeneity bias.

Table 9-1 summarizes the estimates and diagnostics of the instrumental variable listed in equation 1. The three columns of table 9-1 differ only in terms of what fixed effects are used. Column 1 shows how only firm-level fixed effects are used, column 2 year fixed effects only, and in column 3 we see both firm and year fixed effects. It is worth noting that results are not statistically significant when using both unit and time fixed effects. Interestingly, when looking individually at unit level or time only fixed effects we see that the lagged coefficient Non_Routine_1 is statistically significant in both cases. However, estimates are statistically significant at ($p<0.01$) levels when using year only fixed effects, while they are statistically significant only at ($p < 0.1$) when using firm only fixed effects. Moreover, there is a greater substantive effect when we account for time only fixed effects, versus unit only fixed effects. In the former case we see how for every additional certified non-routine LCA visa issued to a given firm (lagged by one time period), there is a corresponding 0.25 unit increase in reports listing immigration as lobbying issue by said firm, all else being equal. By contrast, when we look at the unit only fixed effects, we see that for every additional certified non-routine LCA visa issued to firm (lagged by one time period), there is a corresponding 0.07 unit increase of reports listing immigration as lobbying issue by said firm, all else being equal.

Table 9-1: 2SLS Lagged by One Year with Firm and Time Level Fixed Effects

	Total.Immigration.Lob		
Model:	(1)	(2)	(3)
Variables			
Non.Routine_1	0.0666*	0.2481***	0.0970
	(0.0357)	(0.0332)	(0.0707)
lobbied_1	0.0668	0.0073	0.1019
	(0.1085)	(0.1173)	(0.1535)
Trade.Union.Representation_1	-0.0069**	-0.0019*	-0.0037
	(0.0034)	(0.0009)	(0.0033)
Fixed Effects?	Firm	Year	Firm and Year
Fit statistics			
R^2	0.76282	-0.30707	0.74801
F-test (1st stage), Non.Routine_1	69.675***	65.838***	20.506***
Wu-Hausman	8.1136***	24.929***	4.2728**

$^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$
Fixed effects estimated but not shown in Fixed Effects column
Cluster-robust standard errors are used.

What is also worth noting in table 9-1 are the diagnostics, seen towards the bottom of the table. Specifically, we see the F-test, on the instrument in the first stage, where the null hypothesis posits that we have a weak instrument. Ergo, when results are statistically significant, these are suggestive that we have a strong instrument. Furthermore, there is the Wu-Hausman test, often used to gauge for endogeneity. If the Wu-Hausman yields statistically significant estimates, we can reject the null hypothesis, and assume that there is an endogenous relationship if we were to use a basic OLS model between our independent and dependent variables, in this case between the number of certified LCA visas issued to non-routine occupations, and the number of immigration lobbying reports by firm. In short, the Wu-Hausman test suggests that we are warranted in using an instrumental variable in lieu of OLS.

Equation 2: 2SLS With Time and Unit Fixed Effects (instrument lagged by two time periods)

First Stage:

$$\text{Non. Routine}_{i,y-1} = \iota_0 + \iota_1 \text{log\_cap\_exp}_{i,y-2} + \iota_2 \text{lobbied}_{i,y-1} + \iota_2 \text{Trade. Union. Rep.}_{i,y-1} + \Lambda_i + \Gamma_y + \Psi_{i,y-1}$$

Second Stage

$$\text{Total. Immigration. Lob}_{i,y} = \sigma_0 + \sigma_1 \text{Non.} \widehat{\text{Routine}}_{i,y-1} \;\; \sigma_2 \text{lobbied}_{i,y-1} + \sigma_3 \text{Trade. Union. Rep.}_{i,y-1} + \Lambda_i + \Gamma_y + \Omega_{i,y-1}$$

Equation 2 basically mirrors equation 1, albeit with the difference that the instrument is lagged by 2 time periods, while the endogenous regressor and controls are lagged by one time period. The logic here being that, for example, firm capital expenditures in 2009, may impact the labor composition of firms (i.e., certified non-routine foreign-born workers) in 2010, as the LCA application process can take up to 13 months (The UCSF H-1B Process and Processing Times n.d.). Thus, to account for duration of applications, the instrument is lagged by two time periods, as seen in equation 2. As with equation 1, in equation 2 I include time and unit (firm) level fixed effects.

When looking at Table 9-2, we notice some changes. On the one hand we see that there is a statistically significant relationship between Non.Routine_1 and Total.Immigration.Lob, when looking at firm only, year only, and firm and year fixed effects. Now, when looking at firm only fixed effects we see that for every additional certified non-routine LCA visa issued to firm (lagged by one time period), there is a corresponding 0.09 unit increase in reports listing immigration as lobbying issue by said firm, all else being equal, at (p<0.05) levels. When looking at year only fixed effects, estimates remain fairly similar in column 2 of table 9-2, compared to column 2 of table 9-1.

Table 9-2: 2SLS (Instrument Lagged by Two Years) with Firm and Time Level Fixed Effects

	Total.Immigration.Lob		
Model:	(1)	(2)	(3)
Variables			
Non.Routine_1	0.0819**	0.2475***	0.1247**
	(0.0391)	(0.0352)	(0.0553)
lobbied_1	0.0280	0.0092	0.0530
	(0.1117)	(0.1036)	(0.1255)
Trade.Union.Representation_1	-0.0073**	-0.0019*	-0.0037
	(0.0036)	(0.0009)	(0.0036)
Fixed Effects?	Firm	Year	Firm and Year
Fit statistics			
R^2	0.75175	-0.30501	0.72175
F-test (1st stage), Non.Routine_1	59.221***	75.355***	39.091***
Wu-Hausman	9.7796***	28.395***	12.790***

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$
Fixed effects estimated but not shown in Fixed Effects column
Cluster-robust standard errors are used.

Interestingly enough, when looking at firm and year fixed effects (column 3 of table 9-2), we see that estimates are statistically significant for Non_Routine_1, where for every additional certified non-routine immigration visa issued to a firm (lagged by one time period) there is a corresponding 0.12 unit increase in lobbying reports listing immigration as lobbying issue. By lagging the instrument by two time periods, and lagging the explanatory variables by one time period, we may be actually addressing questions of unobserved heterogeneity better. Like with table 9-1, the diagnostics in table 9-2 suggests that we have an endogenous relationship between certified LCA visas issued to non-routine occupations and the number of immigration lobbying reports by firm. Furthermore, the F-test reveals, that we can reject the null hypothesis that log capital expenditure is a weak instrument.

Table 9-3: 2SLS Lagged by One Year with Firm and Time Level Fixed Effects

	log_imm_lob_amount		
Model:	(1)	(2)	(3)
Variables			
Non.Routine_1	0.1211**	0.2629***	0.1770
	(0.0600)	(0.0306)	(0.1262)
lobbied_1	0.0376	0.5107**	0.0746
	(0.1726)	(0.1714)	(0.2499)
Trade.Union.Representation_1	-0.0047	0.0098***	0.0001
	(0.0053)	(0.0022)	(0.0060)
Fixed Effects?	Firm	Year	Firm and Year
Fit statistics			
R^2	0.51732	-0.28933	0.47449
F-test (1st stage), Non.Routine_1	69.675***	65.838***	20.506***
Wu-Hausman	8.6796***	26.714***	5.0531**

$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$
Fixed effects estimated but not shown in Fixed Effects column
Cluster-robust standard errors are used.

However, what if instead of looking at reports listing immigration, we focused instead on firms' lobbying expenses, when immigration is listed as a lobbying issue. Although looking at lobbying amount is not indicative, necessarily of how much money a firm spent lobbying on immigration, as discussed in the previous section, firms' lobbying expenses can at least inform us that a firm was willing to incur costs associated with the lobbying issues listed, including immigration. In other words, the firm in question was willing to invest so much in terms of lobbying costs, to include among its lobbying issues, the question of immigration.

Tables 9-3 and 9-4 are similar to tables 9-1 and 9-2 in terms of the explanatory variables and instruments we use. The main difference is that now in tables 9-3 and 9-4 we are looking at the natural logarithm of immigration lobbying expenses incurred by a given firm *i* in year *y*. For Table 9-3, we follow a similar logic to the one shown in equation 1, with the only difference being that our outcome variable now is log_imm_lob_ammount instead of

Total.Immigration.Lob . In column 1 of Table 9-3, we see that when we use firm-only fixed effects, for every unit increase in the number of Certified, non-routine visas issued to a given firm (lagged by one time period) there is a corresponding 0.12 percent increase in lobbying spending associated with immigration, at statistically significant levels ($p<0.05$). When looking at firm-only fixed effects, estimates for lobbied and Trade.Union.Representation are not statistically significant. However, when we look at year only fixed effects (column 2 from Table 9-3) we see that all results are statistically significant. In the case of non_routine_1, we now see that for every unit increase in certified non-routine LCA visas, there is a corresponding 0.26 percent increase in lobbying spending associated with immigration, at statistically significant levels ($p<0.01$). Yet in column 3 of table 9-2, where we include both firm and year fixed effects, results are no longer statistically significant.

On the other hand, when we look at Table 9-4, we are now dealing, like in Table 9-2, with the instrument being lagged by two time periods, while the explanatory variables are being lagged only by one time period, albeit with log_imm_lob_ammount outcome variable (in Table 4). While columns 1 and 2 of table 9-4 produce results similar to columns 1 and 2 in table 9-3, we now see in column 3 (of table 9-4) a statistically significant relationship between the number of Certified LCA visas and immigration-lobbying spending by firm. In this case, for every additional certified LCA visa issued to a firm (lagged by one time period) there is a corresponding 0.23 percent increase in lobbying activity associated with immigration ($p<0.01$). Given that we obtain more significant results when we lag our instrument by two time periods and our explanatory variables by one time period, we may still be dealing with omitted variable bias or a misspecified model.

It is worth noting though, even if we have statistically significant findings, substantively speaking, the relationship between our main explanatory variables for and our main outcome variables in Tables 9-1 through 9-4, are close to 0. This may very well be because we have information on 3,653 units, however, for all of these units we do not always find information on immigration lobbying. Furthermore, given that we have thirteen years of data versus 281 firms, that including only time-level fixed effects yields for us results that are statistically significant. Including firm fixed effects, to control for unobserved unit-heterogeneity, may paradoxically also control for all differences among firms, which would make any type of analysis more difficult.

Table 9-4: 2SLS (Instrument Lagged by Two Years) with Firm and Time Level Fixed Effects

	log_imm_lob_amount		
Model:	(1)	(2)	(3)
Variables			
Non.Routine_1	0.1572**	0.2737***	0.2262**
	(0.0690)	(0.0343)	(0.1008)
lobbied_1	-0.0540	0.4753***	-0.0123
	(0.1914)	(0.1513)	(0.2113)
Trade.Union.Representation_1	-0.0056	0.0099***	0.0002
	(0.0056)	(0.0023)	(0.0066)
Fixed Effects?	Firm	Year	Firm and Year
Fit statistics			
R^2	0.47943	-0.32875	0.40588
F-test (1st stage), Non.Routine_1	59.221***	75.355***	39.091***
Wu-Hausman	12.271***	33.889***	15.656***

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$
Fixed effects estimated but not shown in Fixed Effects column
Cluster-robust standard errors are used.

We see then the importance for more specific and accurate data that measures with greater specificity questions of technology input at the firm-level, types of labor employed (including foreign-workers), and whether they (the firms) incur costs associated with promoting immigration policies favorable to their production interests, including questions about expenditures on immigration lobbying. At the moment, capital expenditures constitute measures that are quite large (billions of dollars in some cases) and too broad.

Although for the purpose of this project there are some data limitations, this in turn provides an opportunity to produce detailed data that reveals the types of technology firms use, the types of foreign workers firms hire, and the extent to which they lobby in questions of immigration. In short, this is an opportunity to develop original data on firms' labor, production, and lobbying activity as a future project.

CHAPTER 10. CONCLUSION

10.1 Dissertation Overview

This dissertation has focused on the qualified effects of new technologies – for example, automation and AI – on firms' immigration policy preferences. The motivation for this project was multifold. In line with the Open Economy Politics (OEP) literature and the work by Margaret Peters, immigration policy has been examined through the lens of international political economy.

Considerable literature has been devoted to explaining immigration and immigration policy to the United States as driven by public opinion, political polarization, and on-going political gridlock. However, this dissertation calls attention in the ways by which the major actors who generally lobby for immigration tend to be firms motivated more by economic incentives than social actors informed by cultural issues. The ubiquity of firm-lobbying in contemporary American politics warrants further analysis onto the factors that influence firm immigration lobbying. Moreover, understanding how automation affects firms' immigration policy preferences helps further elucidate our understanding of the types of social changes the "Fourth Industrial Revolution" is producing.

My main argument is that as technologies increase demand for non-routine labor, we should expect this to influence firms' immigration policy preferences, especially among firms for which immigrants constitute an important labor component. Per the scholarship of authors like Daron Acemoglu and David Autor, new technologies increase demand for labor in non-routine occupations, which can be both low-skilled and high-skilled occupations. Given that immigrant workers to the United States concentrate primarily in low-skilled or high-skilled occupations, I argue that we can expect a positive relationship between automation and firm-immigration lobbying for non-routine workers, who could be low-skilled as well as high-skilled.

One of the biggest limitations for this research project was access to reliable consistent panel or longitudinal data on technology implementation and its effects on labor at the firm level. A comprehensive analysis on firm automation and immigration lobbying, would have to be longitudinal, as to better capture intra-firm variation on production, labor needs, and immigration-lobbying. Thus, the absence of reliable consistent panel data on technology, labor, and companies currently represents an important limitation, not only to this project, but also to other researchers that aim to assess more precisely the impacts automation has on labor at the firm level in general.

The data that are available are either new and aggregate, as seen with the Annual Business Survey (ABS) discussed in Chapter 7, or too broad as was the case with firm-level capital expenditures used for analysis in chapters 8 and 9. However, these data limitations represent an opportunity not an obstacle, as there is room to produce more rigorous longitudinal surveys monitoring the implementation of new technologies and their effects on labor.

In chapters 8 and 9, we do see a positive correlation between firm-level capital spending and immigration lobbying. After controlling for unobserved heterogeneity, reversed causality, and omitted variables, we see that an increase in firm-capital expenditure is conducive to greater immigration lobbying, especially among firms that employ primarily non-routine high-skilled immigrant workers.

10.2 Implications and Future Research

This dissertation calls attention to the need to analyze and theorize the transformative effects that new technologies like AI and automation are having globally. Politically, socially, and economically, we find ourselves flying blind, as Klaus Schwab suggested, in an era of great technological innovation and transformation. Although human beings make decisions about production, including the decision of what types of technology to develop, historically the advent of new technologies has always produced numerous social and political alterations to existing status quos. The First Industrial Revolution, with the introduction of mechanization and the assembly line, had profound consequences in international relations, ranging from trade to war.

The fact that we are "flying blind" means that we are overlooking ongoing changes in the international landscape, which could have profound implications regarding the existing international order and norms. As demand for non-routine labor continues to grow, will this for example, impact international norms regarding immigration, trade, or international security?

Will greater reliance on automation increase global migration, especially as more developing economies rely on new technologies to meet their production needs? Will technologies like automation and AI, force international negotiations regarding what is permissible in war, as has happened with chemical, biological, and nuclear weapons in the past? There is certainly plenty of room for more analysis and documentation of new technologies and automation economically, socially, and politically.

Lastly, there should be also reflection and re-evaluation of the assumptions held in many models like the Task-Based models used in economics. In any good research model or theory, there are always assumptions and simplifications made for the sake of parsimony about the world. Theories are at the end of the day like "banisters" that we can use to lean on and make inferences about the world. However, all theories are fundamentally heuristics or models that present simplified renditions of the world. As models, it is important that scholars not conflate theories with reality itself, i.e., reified theory.

When theories are reified, they are elevated to the level of canon, even doctrine in academic circles, preventing alternative theories that hold different assumptions and modes of analysis, into the fore of the mainstream. While it is important to ensure for the sake of theoretical consistency that research programs test empirically the claims derived from commonly held premises; it is also important to allow for a diversity of perspectives, and academic heterodoxy that is open to innovation and re-evaluation of methods and assumptions to research programs.

The question of routineness and non-routineness of a task and occupation can of course be critiqued on different levels. Perhaps the biggest critique refers to the endogeneity of the model itself. On the one hand, changes in technology are what renders certain actions and tasks routine/non-routine. That is, the more sophisticated computer algorithms and robotics become, the more they stand to be able to reproduce a series of tasks once performed by humans. On the other hand, the more routine an occupation becomes, the more they are prone to be displaced by other types of technologies. In other words, machines make an occupation routine, but the level of routineness is what predicts whether other machines will replace workers from these occupations.

We should not assume these discussions as condemnation or invalidation of this theory. Rather, as with the data, there is an opportunity to innovate and refine our understanding of how new technologies are shaping our environment. In short, this dissertation hopes at the very minimum to show the importance, promise, and salience regarding new theories and empirical analysis on the effects of automation on international relations. Despite the fact that other disciplines like economics, sociology, and philosophy have taken great interest in developing scholarship regarding the fourth industrial revolution, in international relations and political science, we continue to "fly blind." But all this means that there is great opportunity to enhance and even produce new research agendas and even "paradigms" that help explain the effects of technology within the context of the literature of international relations.

APPENDIX

Table A-1: Top-Twenty Immigration Lobbying Clients[91]

Client Name	Total Immigration Reports Filed (1998-2020)	Is a Firm	Is a Trade Association	Lobbied Favorably For Immigration	Lobbied Against Immigration
Microsoft Corp.	591	X		X	
Oracle America Inc.	214	X		X	
Intel Corp.	185	X		X	
AmericanHort	172		X	X	
Cognizant Technology Solutions	167	X		X	
Perspecta	150	X		X	
U.S. Travel Association	143		X	X	
Qualcomm Inc.	141	X		X	
Wing Formerly X Google Inc.	141	X		X	
Accenture Lip	136	X		X	
Techserve Alliance	136		X	X	
National Association of Home Builders	127		X	X	
Business Roundtable	126		X	X	

[91] Composed using Lobby View data: Kim, In Song (2018). "LobbyView: Firm-level Lobbying & Congressional Bills Database." Working paper available from http://web.mit.edu/insong/www/pdf/lobbyview.pdf.

Entertainment Software Association	123		X	X	
Consumer Electronics Association	117		X	X	
Texas Instrument Association	115	X		X	
National Restaurant Association	110		X	X	
U.S. Chamber of Commerce	109		X	X	
NumbersUSA	108		X		X
Facebook	106	X		X	

Table A-2: Lobbying Issues and Lobbying Issue Codes[92]

Code	Description	Code	Description
ACC	Accounting	HOM	Homeland Security
ADV	Advertising	HOU	Housing
AER	Aerospace	IMM	Immigration
AGR	Agriculture	IND	Indian/Native American Affairs
ALC	Alcohol & Drug Abuse	INS	Insurance
ANI	Animals	LBR	Labor Issues/Antitrust/Workplace
APP	Apparel/Clothing Industry/Textiles	INT	Intelligence and Surveillance
ART	Arts/Entertainment	LAW	Law Enforcement/Crime/Criminal Justice
AUT	Automotive Industry	MAN	Manufacturing
AVI	Aviation/Aircraft/Airlines	MAR	Marine/Maritime/Boating/Fisheries
BAN	Banking	MED	Medical/Disease Research/Clinical Labs
BNK	Bankruptcy	MIA	Media (Information/Publishing)
BEV	Beverage Industry	MMM	Medicare/Medicaid
BUD	Budget/Appropriations	MON	Minting/Money/Gold Standard
CAW	Clean Air & Water (Quality)	NAT	Natural Resources
CDT	Commodities (Big Ticket)	PHA	Pharmacy
CHM	Chemicals/Chemical Industry	POS	Postal
CIV	Civil Rights/Civil Liberties	RRR	Railroads
COM	Communications/Broadcasting/Radio/TV	RES	Real Estate/Land Use/Conservation
CPI	Computer Industry	REL	Religion
CSP	Consumer Issues/Safety/Protection	RET	Retirement
CON	Constitution	ROD	Roads/Highway
CPT	Copyright/Patent/Trademark	SCI	Science/Technology
DEF	Defense	SMB	Small Business
DOC	District of Columbia	SPO	Sports/Athletics
DIS	Disaster Planning/Emergencies	TAR	Miscellaneous Tariff Bills
ECN	Economics/Economic Development	TAX	Taxation/Internal Revenue Code
EDU	Education	TEC	Telecommunications
ENG	Energy/Nuclear	TOB	Tobacco

[92] For more information, please see: https://lda.congress.gov/ld/help/default.htm?turl=Documents%2FAppCodes.htm.

ENV	Environmental/Superfund	TOR	Torts
FAM	Family Issues/Abortion/Adoption	TRD	Trade (Domestic & Foreign)
FIR	Firearms/Guns/Ammunition	TRA	Transportation
FIN	Financial Institutions/Investments/Securities	TOU	Travel/Tourism
FOO	Food Industry (Safety, Labeling, etc.)	TRU	Trucking/Shipping
FOR	Foreign Relations	URB	Urban Development/Municipalities
FUE	Fuel/Gas/Oil	UNM	Unemployment
GAM	Gaming/Gambling/Casino	UTI	Utilities
GOV	Government Issues	VET	Veterans
HCR	Health Issues	WAS	Waste (hazardous/solid/interstate/nuclear)
		WEL	Welfare

Table A-3: Routine Task Intensity Index (Absolute Value)

Occupation Title	SOC-CODE	Routine Task Index	Skill-Level
Art Therapists	29-1129	**1.92**	High Skill
Education Administrators, Kindergarten through Secondary	11-9032	**1.84**	High Skill
Emergency Management Directors	11-9161	**1.81**	High Skill
Chief Sustainability Officers	11-1011	**1.78**	High Skill
Training and Development Specialists	13-1151	**1.78**	High Skill
Coaches and Scouts	27-2022	**1.77**	High Skill
Dental Assistants	31-9091	**1.16**	Middle Skill
Electrical Engineers	17-2071	**1.16**	High Skill
Logistics Analysts	13-1081	**1.16**	High Skill
Nuclear Monitoring Technicians	19-4051	**1.16**	Middle Skill
Robotics Technicians	17-3024	**1.16**	Middle Skill
Shoe Machine Operators and Tenders	51-6042	**0.49**	Low Skill
Machine Feeders and Offbearers	53-7063	**0.47**	Low Skill
Glass Blowers, Molders, Benders, and Finishers	51-9195	**0.46**	Low Skill

Table A-3: Routine Task Intensity Index (Absolute Value)

Occupation Title	SOC-CODE	Routine Task Index	Skill-Level
Court Reporters and Simultaneous Captioners	27-3092	**0.43**	Middle Skill
Woodworking Machine Setters, Operators, and Tenders, Except Sawing	51-7042	**0.41**	Low Skill
Pressers, Textile, Garment, and Related Materials	51-6021	**0.35**	Low Skill

*Source: O*NET® Database Releases Archive at O*NET Resource Center (onetcenter.org)*

Table A-4: Types of Worker Visas

Visa Category	Description of Visa Category
E-1	Issued to individuals from certain countries to enter United States to engage in international trade on their own behalf[93]
E-2	Issued to foreign, long-term investors[94]
E-3	Like the H-1B visa but issued only to citizens of Australia[95]
H-1B	Allows American employers to temporarily employ foreign workers in specific occupations[96]
H-1B1	Like the H-1B visa but issued only to citizens of Singapore and Chile[97]
H-2A	Visa for temporary agricultural workers[98]
H-2B	Issued to non-agricultural services or labor on a one-time, seasonal, peak, or intermittent basis[99]
H-3	Visa that allows noncitizens coming temporarily to the United States as trainees (e.g., medical trainees) or as special education exchange visitors[100]
L-1	Visa for temporary employees of Multinational Corporations (MNCs) that have offices in the United States[101]
O	Visas issued to individuals who possess extraordinary abilities[102]
P	Visas issued athletes, artists, and entertainers[103]
R-1	Visa issued to temporary religious workers[104]

[93] For more information see (E-1 Treaty Traders | USCIS).

[94] For more information see (E-2 Visa: CNMI-Only Investor | USCIS).

[95] For more information see (E-3 Specialty Occupation Workers from Australia | USCIS).

[96] For more information see (H-1B Program | U.S. Department of Labor (dol.gov)).

[97] For more information see (H-1B1 Program | U.S. Department of Labor (dol.gov)).

[98] For more information see (H-2A Visa Program For Temporary Workers | Farmers.gov).

[99] For more information see (H-2B Program | U.S. Department of Labor (dol.gov)).

[100] For more information see (H-3 Nonimmigrant Trainee or Special Education Exchange Visitor | USCIS).

[101] There two types of L-1 visas. There is the L-1A visa, issued to individuals working in managerial or executive position in a company. There is also the L-1B visa, issued to individual working for a company in positions that require specialized knowledge. For more information see (L Visas (L-1A and L-1B) for Temporary Workers | USCIS).

[102] There are different categories of O visas. First, there is O-1A visa issued to individuals with an extraordinary ability in the sciences, education, business, or athletics, (not including the arts, motion pictures, or television industry). There is the O-1B visa, issued to individuals with extraordinary abilities in the arts, motion picture, or the television industry. Lastly, there is also the O-2 issued to individuals who accompany an O-1 artist or athlete to assist in a specific event or performance. For more information see (O-1 Visa: Individuals with Extraordinary Ability or Achievement | USCIS).

[103] It should be noted that there are different categories of P visas. There is P-1 visa, issued to individual or team athletes (P-1A), or members of an entertainment group (P-1B) that are internationally recognized. P-2 visas issued to artists or entertainers who will perform under a reciprocal exchange program. Lastly, there is P-3 visa, issued to artists or entertainers who perform under a program that is culturally unique. For more information, see (Temporary Worker Visas (archive.org)).

[104] For more information see (R-1 Nonimmigrant Religious Workers | USCIS).

TN NAFTA	Issued to citizens of Canada and Mexico due to a NAFTA provision, mandating the simplified entry and employment permission for certain professionals who are citizens from one NAFTA member states into the jurisdiction of another (e.g., Canadian Citizens working in the United States)[105]

[105] For more information see (TN NAFTA Professionals | USCIS).

Table A-5: Routine Task Index (RTI) O*NET Task Measures

To construct the Routine Task Index (RTI) I relied on the O*NET composite task measures following in the line of Acemoglu and Autor (2011) and subsequently by Cirillo et al. (2019) and Guarascio et al. (2018). These composite measures build on the O*NET Abilities[106], Work Activities[107], and Work Context[108], and the Skills[109] Importance scales (for more information on Importance scales see chapter 4). The detailed components of the routine task index (RTI) were constructed using specific measures taken from Abilities, Work Activities, Work Context, and Skills.

Routine Cognitive (RC)

4.C.3.b.7 Importance of repeating the same tasks

4.C.3.b.4 Importance of being exact or accurate

4.C.3.b.8 Structured v. Unstructured work (reverse)

Routine Manual (RM)

4.C.3.d.3 Pace determined by speed of equipment

4.A.3.a.3 Controlling machines and processes

4.C.2.d.1.i Spend time making repetitive motions

Non-Routine Cognitive: Analytical (NRCA)

4.A.2.a.4 Analyzing data/information

4.A.2.b.2 Thinking creatively

4.A.4.a.1 Interpreting information for others

Non-Routine Cognitive: Interpersonal (NRCI)

4.A.4.a.4 Establishing and maintaining personal relationships

4.A.4.b.4 Guiding, directing and motivating subordinates

[106] The O*NET Content Model (see chapter 4 for more information on the O*NET Content Model) defines abilities as the, "relatively enduring attributes of an individual's capability for performing a particular range of different tasks (Fleishman et al. 2003; O*NET OnLine Help: Details Report (onetonline.org)). Abilities are at times referred to as traits, given that abilities tend to remain stable and constant over time (FR-10-41 (onetcenter.org)).

[107] Per the O*NET Content Model, work activities summarize the kinds of tasks that may be performed by workers across multiple occupations (O*NET OnLine Help: Details Report (onetonline.org). For more information, see (C:\Home\ONET\DWA_summary.prn.pdf (onetcenter.org)).

[108] Work context is used to refer to the physical and social factors that influence the nature of work (O*NET OnLine Help: Details Report (onetonline.org)).

[109] Skills are developed capacities that facilitate learning and the performance of activities that occur across jobs (O*NET OnLine Help: Details Report (onetonline.org)).

4.A.4.b.5 Coaching/developing others

Non-Routine Manual Physical (NRM)

4.A.3.a.4 Operating vehicles, mechanized devices, or equipment

4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls

1.A.2.a.2 Manual dexterity

1.A.1.f.1 Spatial orientation

Non-Routine Manual Interpersonal (NRMI)

2.B.1.a Social Perceptiveness

Figure A-1: ABS 2017 Use of Business Technology

BUSINESS TECHNOLOGIES

In 2017, to what extent did this business use the following technologies in producing goods or services?

Select one for each row.

	No use	Testing but not using in production or service	In use for less than 5% of production or service	In use for between 5% - 25% of production or service	In use for more than 25% of production or service	Don't know
a. Augmented reality						
b. Automated guided vehicles (AGV) or AGV systems						
c. Automated storage and retrieval systems						
d. Machine learning						
e. Machine vision software						
f. Natural language processing						
g. Radio-frequency identification (RFID) inventory system						
h. Robotics						
i. Touchscreens/ kiosks for customer interface (Examples: self-checkout, self-check-in, touchscreen ordering)						
j. Voice recognition software						

Source: abs_2018.pdf (census.gov)

Figure A-2: ABS 2018 Use of Business Technology

INFORMATION ONLY - DO NOT USE TO REPORT

E.3 Production Technology for Goods and Services

During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?

Artificial Intelligence

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

Cloud-Based Computing Systems and Applications

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

Specialized Software

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

Robotics

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

Specialized Equipment

- ☐ Did not use
- ☐ Tested, but did not use in production or service
- ☐ Low use
- ☐ Moderate use
- ☐ High use
- ☐ Don't know

If all answers to **E.3** are **"Did not use"**, **"Tested, but did not use in production or service"**, or **"Don't know"** then proceed to **E.19 – Factors Adversely Affecting Technology Adoption and Utilization** on page 30.

If answers for **Artificial Intelligence** are "Low Use", "Moderate Use", or "High Use" then answer questions E.4 – E.6 on page 25.

If answers for **Cloud-based Computing Systems and Applications** are "Low Use", "Moderate Use", or "High Use" then answer questions E.7 – E.9 on page 26.

If answers for **Specialized Software** are "Low Use", "Moderate Use", or "High Use" then answer questions E.10 – E.12 on page 27.

If answers for **Robotics** are "Low Use", "Moderate Use", or "High Use" then answer questions E.13 – E.15 on page 28.

If answers for **Specialized Equipment** are "Low Use", "Moderate Use", or "High Use" then answer questions E.16 – E.18 on page 29.

Form ABS-1

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Source: abs_2019.pdf (census.gov)

Table A-6: List and Description of Surveyed Technologies in the 2018 ABS (consisting of data collected in 2017)[110]

Technology Name	Description
Augmented Reality	Technology that provides a view of real-world environment with computer-generated overlays.
Automated Guided Vehicle (AGV)	Computer-controlled transport vehicle that operates without a human driver. AGVs navigate facilities using software and censors.
Automated Storage and Retrieval System	Technology that locates, retrieves, and replaces items from predetermined storage locations.
Machine Learning	Technology used to provide image-based automatic inspection, recognition or analysis
Natural Language Processing	Technology that allows a computer to process human speech or text
Radio Frequency Identification System (RFID)	System of tags and readers used for identification and tracking. Tags store information and transmit those using radio.
Robotics	Reprogrammable machines capable of automatically carrying out a complex set of actions.
Touchscreens/Kiosks (for customer interface, e.g., self-checkout)	A computer with a touchscreen that allows a customer to receive information or perform a task related to the business such as registering for a service or purchasing items.
Voice Recognition Software	Software that converts speech to texts or executes simple commands based on a limited vocabulary or executes more complex commands when combined with natural language processing.

[110] For more information please see: 2018_abs_instruction_guide.pdf (census.gov), p. 27-28.

Table A-7: List and Description of Surveyed Technologies in the 2019 ABS (consisting of data collected in 2018)[111]

Technology Name	Description
Artificial Intelligence (AI)	AI is a branch of computer science and engineering devoted to making machines intelligent, in so far as those machines are able to perceive, analyze, determine response and act appropriately in its environment. Systems with AI can perform functions including, but not limited to, speech recognition, machine vision, or machine learning. AI technologies also include virtual agents, deep learning platforms, decision management systems, biometrics, text analytics, and natural language generation processing.
Cloud-Based Computing Systems and Applications	Cloud computing enables ubiquitous, convenient, on-demand internet access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction
Specialized Software (excluding Artificial Intelligence)	Specialized software is custom or packaged software dedicated to performing a particular business function. Specialized software includes, but is not limited to, software applications for accounting, sales, marketing, customer service and billing, logistics, health care delivery, telemedicine, computer-aided design (CAD), computer-aided engineering (CAE), or inventory management.
Robotics	Automatically controlled, reprogrammable, and multipurpose machines used in automated operations in industrial and service environments. A robot may be part of a manufacturing cell or incorporated into another piece of equipment. Industrial robots may perform operations such as: palletizing, pick and place, machine tending, material handling, dispensing, welding, packing/repacking, and cleanroom. Service

[111] For more information please see: abs_2019.pdf (census.gov), p. 40.

	robots are commonly used in businesses for such operations as cleaning, delivery, construction, inspection, and medical services such as dispensing or surgery
Specialized Equipment (excluding Robotics)	Specialized equipment refers to equipment capable of automatically carrying out pre-specified task(s). Specialized equipment includes, but is not limited to, computer numerically controlled (CNC) machinery, computer-aided manufacturing (CAM) systems, manufacturing cells, materials working lasers, automated guided vehicles systems, automated storage and retrieval systems, and automated materials handling systems.

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